Leveraging Machine Learning and Computer Vision for Advanced UAV Communications

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Abstract

In the rapidly developing field of wireless communication, there is a growing demand for technologies that can provide flexible deployment, extended coverage, and enhanced performance in next-generation networks. Traditional networks often struggle with high mobility and environmental blockages, highlighting the need for innovative solutions like Unmanned Aerial Vehicles based (UAV-based) dynamic base stations. UAVs offer a promising solution by functioning as dynamic base stations in 5G and 6G networks, with the potential to address these challenges and improve communication reliability and efficiency.

However, the integration of UAVs into wireless communication presents significant challenges. Ensuring reliable communication in high-mobility environments, optimizing beam management techniques, predicting blockages in real time, and managing the latency inherent in UAV-assisted networks all require innovative solutions. These challenges are combined by the need to balance power consumption and processing capacity, especially when performing complex tasks such as on-device machine learning and computer vision-based beamforming.

The first study of this dissertation focuses on the challenge of beam management in milimeter wave (mmWave) 5G and beyond networks, where speedy environmental changes in high-mobility scenarios degrade signal quality. Previous studies have highlighted the limitations of traditional beamforming approaches, especially in their ability to adjust to dynamic environments. To enhance this, a novel technique is proposed that integrates computer vision (CV) with ensemble learning, employing the "you look only once" (YOLO-v5) for precise UAV detection and positioning. By stacking two neural networks to refine a meta-learner, this method achieves approximately 90% top-1 accuracy in K-beam predictions, significantly enhancing the signal-to-noise ratio and improving network performance in high-mobility scenarios.

The second study focuses on the problem of proactive blockage prediction and management in mmWave communications, where maintaining line-of-sight connectivity is necessary. Previous studies have stated that traditional reactive handover methods often result in service disruptions due to unexpected blockages. Computer vision techniques used previously resulted to a 40% improvement in user connectivity by predicting and managing blockages. Extending this concept, the study addresses proactive blockage prediction and management in mmWave communications, employing UAVs not only as base stations but also as proactive agents in handover processes. By leveraging CV to detect potential blockages and monitor user movement, the system facilitates proactive handovers to maintain line-of-sight connectivity. This approach, evaluated using a publicly available dataset and incorporating advanced antenna modeling techniques, has demonstrated a 20% enhancement in network performance.

The third study reveals a new approach that utilizes vision-aided machine learning for efficiently and precisely predicting the optimum beam orientations for UAVs using mmWave and terahertz (THz) technologies. Previous research has shown that, while utilizing visual data from UAVs can increase beam prediction accuracy, there are still issues in reducing beam training overhead and managing real-time mobility. Employing data from UAV cameras, the proposed method achieves approximately 90% accuracy in predicting the best beam direction for the top-1, and nearly 100% for the top-3. Performing these computations directly on the UAV (on-device inference) reduces communication delays by 15% and lowers the cost of communication by 50% in terms of power consumption in comparison with ground-based processing, greatly increasing the efficiency of real-time UAV communication. Collectively, these studies underline the potential of using UAVs to improve wireless communication providing innovative solutions for network expansion, precise beam management, and proactive blockage prediction.

This thesis emphasizes UAVs as a cornerstone technology for advancing future wireless communication, setting the stage for more reliable, efficient, and comprehensive communication systems.

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List of Abbreviations

1G First Generation of Mobile Communication

2G Second Generation of Mobile Communication

3G Third Generation of Mobile Communication

4G Fourth Generation of Mobile Communication

5G Fifth Generation of Mobile Communication

6G Sixth Generation of Mobile Communication

UAV Unmanned Aerial Vehicle

IoT Internet of Things

QoS Quality of Service

BS Base Station

AMPS Advanced Mobile Phone System

NMT Nordic Mobile Telephone

TACS Total Access Communications System

JTACS Japan's Total Access Communications System

FDMA Frequency Division Multiple Access

GSM Global System for Mobile Communications

CDMA Code Division Multiple Access

UMTS Universal Mobile Telecommunications System

WCDMA Wideband Code Division Multiple Access

LTE Long-Term Evolution

MEC Mobile Edge Computing

XR Extended Reality

RL Reinforcement Learning

D2D Device-to-Device Communication

UE User Equipment

SINR Signal-to-Interference-plus-Noise Ratio

RSS Received Signal Strength

SL Straight Line

RW Random Walk

RWP Random Waypoint

RD Random Direction

M-RD Modified Random Direction

ANR Automatic Neighbor Relation

NRT Neighbor Relation Table

GHO Group Handover

URLLC Ultra-Reliable Low-Latency Communication

RGB-D RGB-Depth

YOLO You Only Look Once

GRU Gated Recurrent Unit

OFDM Orthogonal Frequency Division Multiplexing

ULA Uniform Linear Array

LoS Line of Sight

THz Terahertz

Tx Transmitter

Rx Receiver

RSSI Received Signal Strength Indicator

CU Control Unit

SBS Small Base Station

ODL Object Detection and Localization

Tblk Time to Block

THO Time to Handover

Texec Time to Execute

Tw Time Waiting

CNN Convolutional Neural Network

FPGA Field-Programmable Gate Array

AR Augmented Reality

AP Access Point

ViWi Vision-Wireless Integration Framework

SE-ResNet50 Squeeze-and-Excitation ResNet50

List of Publications

Here I present a list of research articles that I have written or authored since June 2021, when I began my doctoral studies. The names, authors, publication intities, and current status of each article are listed in detail below.

Journal:

1. **Iftikhar Ahmad,** Ahsan Raza Khan, Muhammad Ali Imran, Ahmed Zoha, and Sajjad Hussain. "Latency-Aware On-Device Machine Learning for Vision-Aided Beam Prediction in mmWave UAV Communication" **(Under Review)**.

2. **Iftikhar Ahmad,** Ahsan Raza Khan, Abdul Jabbar, Muhammad Alquraan, Lina Mohjazi, Masood Ur Rehman, Muhammad Ali Imran, Ahmed Zoha, and Sajjad Hussain. "Proactive Blockage Prediction for UAV assisted Handover in Future Wireless Network." arXiv preprint arXiv:2402.04332 (2024) **(Under Review)** .

3. Attai Ibrahim Abubakar, **Iftikhar Ahmad,** Kenechi G. Omeke, Metin Ozturk, Cihat Ozturk, Ali Makine Abdel-Salam, Michael S. Mollel, Qammer H. Abbasi, Sajjad Hussain, and Muhammad Ali Imran. 2023. "A Survey on Energy Optimization Techniques in UAV-Based Cellular Networks: From Conventional to Machine Learning Approaches" Drones 7, no. 3: 214. https://doi.org/10.3390/drones7030214

4. Ahsan Raza Khan, **Iftikhar Ahmad,** Lina Mohjazi, Sajjad Hussain, Rao Naveed Bin Rais, Muhammad Ali Imran, and Ahmed Zoha. "Latency-aware blockage prediction in vision-aided federated wireless networks." Frontiers in Communications and Networks 4 (2023): 1130844.

5. Attai Ibrahim Abubakar, Michael S. Mollel, Oluwakayode Onireti, Metin Ozturk, **Iftikhar Ahmad,** Syed Muhammad Asad, Yusuf Sambo, Ahmed Zoha, Sajjad Hussain, Muhammad Ali Imran, Coverage and throughput analysis of an energy efficient UAV base station positioning scheme, Computer Networks, Volume 232, 2023, 109854, ISSN 1389-1286, https://doi.org/10.1016/j.comnet.2023.109854.

Conference:

1. **Iftikhar Ahmad,** et al., "UAV-assisted 5G Networks for Optimised Coverage Under Dynamic Traffic Load," 2022 IEEE International Symposium on Antennas and Propagation and USNC-URSI Radio Science Meeting (AP-S/URSI), Denver, CO, USA, 2022, pp. 1692-1693, doi: 10.1109/AP-S/USNC-URSI47032.2022.9886848.

2. **Iftikhar Ahmad,** , A. R. Khan, R. N. B. Rais, A. Zoha, M. A. Imran and S. Hussain, "Vision-Assisted Beam Prediction for Real World 6G Drone Communication," 2023 IEEE 34th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Toronto, ON, Canada, 2023, pp. 1-7.

Book Chapter:

1. **Ahmad, Iftikhar,** Ahsan Raza Khan, Rao Naveed Bin Rais, Muhammad Ali Imran, Sajjad Hussain, and Ahmed Zoha. "Multimodal Beam Prediction for Enhanced Beam Management in Drone Communication Networks." Multimodal Intelligent Sensing in Modern Applications (2024): 165-179.

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Declaration

Name: Iftikhar Ahmad
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I hereby declare that the thesis titled "Leveraging Machine Learning and Computer Vision for Advanced UAV Communications" is my work, conducted under the supervision of Prof. Sajjad Hussain at the University of Glasgow. This work has not been submitted for any other degree or professional qualification and is original, except where due reference is made. All sources and resources utilized in this thesis are properly acknowledged, and ethical guidelines have been adhered to in the conduct of this research. This declaration affirms the authenticity of the work presented herein.

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Chapter 1

Introduction

Cellular networks have undergone multiple phases of evolution, progressing from the initial first-generation (1G) systems to the present fifth-generation (5G) technologies. This evolution has been driven by the continuous growth in both the quantity and variety of connected devices, mobile subscribers, and the emergence of data-intensive applications such as online gaming, live video streaming, social media platforms, and more [1]. In 2010, the total usage of mobile data worldwide was 7.462 EB per month. However, current projections suggest that by the year 2030, this figure will increase to 5016 EB per month [2]. These numbers indicate the urgent need for advancements in communication infrastructure.Our society is steadily advancing toward greater dependence on fully automated systems for remote management and control. Self-operating technologies are increasingly becoming a central part in various sectors such as industry, healthcare, transportation, maritime operations, and space exploration [3]. Future wireless communication networks, including 5G and beyond, are anticipated to meet the ever-growing user requirements by addressing the challenges associated with wireless communication. These challenges encompass the demand for faster data speeds, reduced latency, improved reliability, and greater connectivity in order to accommodate several devices [4].

Moreover, it is expected that UAV technology will continue to grow and have a significant influence on how wireless networks develop in the future. UAVs, also known as drones, have evolved from their initial use in military applications to become a useful tool in various civilian and commercial sectors. Their capacity to deliver flexible and cost-efficient communication solutions, surveillance, and data collection makes them a critical component of future networks. However, incorporating UAVs into both current and future communication networks poses unique challenges, such as ensuring seamless communication links, managing the limited battery life of UAVs, and addressing security concerns [5]. Addressing these challenges requires the foundation of innovative solutions, this includes leveraging computer vision (CV) and machine learning (ML) techniques to improve the reliability and performance of UAV communication systems [6].

Machine learning has proven to be a powerful tool in addressing complex problems within wireless communications. Its ability to examine large amounts of data and make predictions in real time provides interesting solutions for optimizing network performance [7]. When combined with vision-aided technologies, machine learning can enable UAVs to autonomously navigate environments, avoid obstacles, and make smart decisions using real-time visual data. This combination of machine learning and vision-aided technologies in UAV communications is expected to revolutionize future networks by providing more efficient, reliable, and secure communication channels [8].

Furthermore, the integration of UAVs with machine learning and vision-aided technologies will likely lead to the development of intelligent, adaptive communication systems able of dynamically adjusting to changing environments and user demands. This will be crucial in maintaining the the rising demand for applications and devices that future networks will need to support. The anticipated growth of smart cities, connected vehicles, Internet of Things (IoT), and other innovations, will further worsen the demand for innovative communication solutions designed to deliver fast, low-latency, and energy-efficient connectivity [9].

In conclusion, as we advance towards a future where communication networks are more interconnected and dependent on autonomous technologies, the role of machine learning and vision-aided UAV communications will become increasingly significant. The development of these technologies is not only essential for meeting the demands of future networks but also for driving innovation in various sectors, ultimately leading to smarter, more efficient, and more flexible communication infrastructures [10].

1.1 Wireless Communication Network Evolution

The initial analog cellular system first-generation (1G) opened the foundation for the evolutionary development of wireless communication networks since it emerged in the 1980s. By 1990, this system was overtaken by the second-generation (2G) digital network, widely known as the "Global System for Mobile Communications (GSM)." Hence, this system carries features like voice communication and SMS. Of course, its limited data rates contributed to the shift to the third generation in 2001 which turned out to offer several times faster data speeds[11, 12]. Considering the evolution of communication technologies throughout the last ten years, it is evident that this journey is not merely about technological progress. Rather, it is about linking people and nations, shaping the world into a unified global community [13].

1.1.1 1G, The First Generation Mobile Network

In 1970s, the introduction of 1G mobile communications marked a significant milestone in wireless technology. 1G networks were primarily analog systems, which facilitated voice communication by modulating radio signals to transmit data. The primary systems utilizing 1G technology included It includes the Total Access Communications System (TACS) in the United Kingdom, the Advanced Mobile Phone System (AMPS) in North America, the

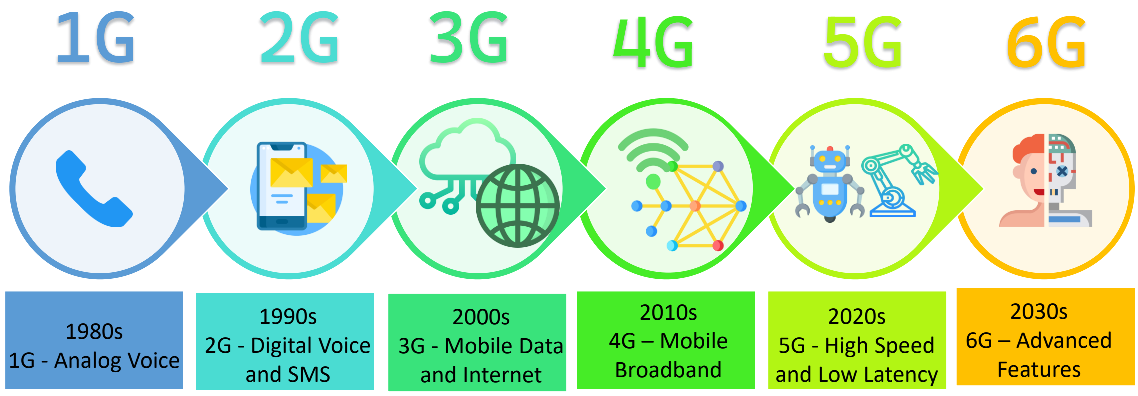

Figure 1.1: Advancement from 1G to 6G.

Nordic Mobile Telephone (NMT) in Scandinavia, and the Total Access Communications System (JTACS) in Japan [14, 15].

Frequency division multiple access (FDMA) was used by AMPS to operate in the 800 megahertz frequency band and assign unique frequencies to individual calls. This system was able of accommodating only a small number of simultaneous users due to the restricted amount of accessible frequencies [16]. Similarly, NMT, developed in Scandinavia, also worked in the 450 megahertz and then the 900 megahertz bands using FDMA [17]. TACS, a variant of AMPS, was introduced in the UK and operated in the 900 MHz band, offering higher capacity by utilizing smaller cell sizes to reuse frequencies more effectively [18]. JTACS, the Japanese adaptation, further optimized the TACS system by adjusting the channel spacing to accommodate the unique demands of the Japanese market [15].

Despite the differences in frequency bands and channel spacing, these systems shared common technical characteristics, such as the use of analog modulation and FDMA for multiple access. However, the analog nature of 1G systems meant that they were prone to issues such as signal interference, limited capacity, and susceptibility to eavesdropping. These limitations underscored the need for more advanced, digital systems, resulting in the development of 2G technology over the following ten years [19].

1.1.2 2G, The Second Generation Mobile Network

The early 1990s saw the emergence of 2G technology, introducing digital technology that significantly improved voice quality and system capacity. This generation also marked the beginning of mobile data services, enabling text messaging (SMS) and limited data transfer. Key 2G technologies were Code Division Multiple Access (CDMA) in the US and the Global System for Mobile Communications (GSM) in Europe, which eventually became the most commonly used standard. By enabling roaming between countries and providing improved security via digital encryption,2G networks set the path for the globalization of mobile communication [14, 20].

1.1.3 3G, The Third Generation Mobile Network

With the emergence of 3G mobile communication in early 2000s, revolutionized the mobile industry by providing high-speed data transfer and supporting multimedia applications. The user experience was greatly improved by 3G networks' capabilities for mobile TV, video calls, and internet access on the go. Prominent 3G protocols included the Universal Mobile Telecommunications System (UMTS) in Europe, which was built on WCDMA technology, and CDMA2000 in the US. 3G technology facilitated the widespread use of mobile broadband services and smartphones, which resulted in a rise in mobile data usage and changed how people communicate and access information [14, 20].

1.1.4 4G, The Fourth Generation Mobile Network

The introduction of 4G mobile communication in the late 2000s, produced a dramatic increase in data speeds and network capacity, enabling a new era of mobile internet services. 4G technology, particularly Long-Term Evolution (LTE), supplied data rates enough for online gaming, streaming high-definition video, and other data-intensive applications. The transition to 4G also saw the introduction of IP-based networks, which improved efficiency and reduced latency. 4G networks supported the rapid growth of mobile apps and services, allowing for seamless connectivity and the proliferation of smart devices. This generation of mobile technology laid the groundwork for the digital economy and the connected world [14, 20].

1.1.5 5G, The Fifth Generation Mobile Network

The late 2010s saw the introduction of the 5G of mobile communication, which marks a substantial advancement in wireless technology. With its extremely fast data rates, minimal latency, and extensive connection, 5G networks pave the way for the creation of cutting-edge applications such as autonomous cars, IoT devices, and smart cities. To enable new use cases and deliver network performance never seen before, 5G technology uses a wide range of frequency bands, including mmWave. Having the capacity to link billions of devices and deliver real-time communication, 5G has the potential to change industries and drive development in a number of fields, from healthcare to manufacturing and beyond [14, 20].

1.1.6 6G, The Sixth Generation Mobile Network

The 6G of mobile communication, anticipated to be fully deployed in 2030s, is expected to revolutionize wireless technology beyond the capabilities of 5G. 6G promises to deliver incredibly fast data rates, very low latency as well as and seamless connectivity over large-scale device networks, including those in the Internet of Everything (IoE). It is probable that this generation will integrate cutting-edge technologies like edge computing, ML, and artificial intelligence (AI) to enable real-time decision-making and automation at unprecedented scales. 6G is envisioned to support holographic communication, immersive extended reality (XR), and advanced automation in industries such as healthcare, manufacturing, and transportation. With the capacity to provide 100 times higher data speeds than 5G and to operate at terahertz (THz) frequencies, 6G will be pivotal in enabling new applications and services that were previously unimaginable, driving the next wave of digital transformation and innovation [21].

1.2 UAVs Emergence in Wireless Communication

UAV incorporation into wireless communication networks has seen substantial growth, driven by their increasing range of applications and unique advantages. In todays rapidly evolving technological landscape, UAVs offer adaptable solutions across various contexts. For instance, UAVs can function as airborne base stations (BS) during disaster recovery or in situations of heightened network demand, ensuring crucial connectivity when traditional infrastructure is compromised. Furthermore, UAVs can operate as aerial user equipment (UE) for tasks such as delivery services or surveillance. Advances in UAV technology have facilitated the widespread deployment of UAVs include aircraft, balloons, tiny planes, drones, and more-all operating in wireless networks. UAVs can offer a wide range of applications with reliable and affordable wireless communications once they are deployed and controlled effectively. They may serve as airborne base stations delivering reliable, on-demand wireless connectivity or engage with ground users as cellular-connected UAVs. This section discusses UAVs applications in wireless communication [22].

1.2.1 Emergency Services (Pop-up Networks)

UAVs are becoming a major focus for commercial development and research due to their potential across various sectors. A key application is in emergency response. In largescale natural disasterssuch as floods, earthquakes, fires, or hurricanesthe destruction of cellular infrastructure often results in the loss of communication services. UAVs can be used to replace lost or damaged base stations, improving the Quality of Service (QoS) for individuals in the affected regions and resuming communication services. UAV parameters, such as trajectories and altitude, can be improved according to user traffic demand and distribution to improve coverage and throughput. For instance, UAVs can create emergency pop-up network to restore connectivity in areas when infrastructure is halted. Reinforcement learning (RL) techniques can be employed to optimize UAV trajectories, improving coverage and speed for ground users [23]. In order to connect remote user groups split apart by natural disasters like earthquakes or floods, UAV base stations (UAV-BSs) can serve as relays. This allows local communication within communities, even when internet access is unavailable. UAVs can also connect inaccessible locations to the internet by offering backhaul services to already-existing wireless networks. Additionally, UAV-BSs can act as backhaul solutions for D2D (device-to-device) communications. Equipped with efficient processors, UAVs can aggregate data in real-time from various devices, aiding in decision-making during emergencies [24]

1.2.2 IoT Devices Data Harvesting

UAVs provide promising IoT application opportunities, particularly in relaying and data harvesting, which has attracted significant research interest. UAVs are especially beneficial in scenarios where IoT devices are placed in remote locations, like offshore regions or rural farmlands, that lack wireless network infrastructure. In these instances, UAVs can assist in data collection and transmission to decision-making centers. The goal of UAV-enabled data harvesting research is to maximize UAV throughput and path planning to ensure adequate data collection before the UAVs battery is depleted. For instance, a deep reinforcement learning framework has been proposed for multi-UAV data collecting systems' path planning, adapting to dynamic network conditions for optimal data collecting from distributed IoT devices, Additionally, research has focused on optimizing UAV trajectory and power supply to ground nodes in data collection systems, with the goal of increasing throughput and coverage probability [25, 26].

This is crucial in situations where IoT devices are placed in areas lacking wireless network infrastructure, including remote farmlands or offshore regions, to help with the data delivery to the decision-making units. Under such circumstances, UAVs can be dispatched to that region to assist in gathering data [27, 28]. The primary focus of research on UAV-enabled data harvesting is on UAV path and throughput optimization to make sure the UAV gathers enough data and gets back to the data center before its battery runs out [29, 30, 31].

In[29], the authors investigated at how to optimize UAV power distribution and trajectory to ground nodes simultaneously to improve speed and coverage probability within a distributed beamforming-based UAV-assisted data collecting system. To achieve optimal performance, they created heuristic algorithms by utilizing approximations and convex optimization, which were designed to optimize the power and identify the best trajectory allocation strategies for maximizing both metrics.

1.2.3 Computation Offloading and Content Caching

These days, content caching is essential to wireless networks, particularly as users can move from one place to another. This procedure include saving crucial information such as usernames, locations, and frequently requested contentat multiple base stations to ensure seamless communication and minimize latency. However, traditional caches are typically stationary, which may not appropriate for extremely mobile users. In such cases, dynamic caching can be carried out through UAV-enabled caching, where UAVs follow cellular devices to offer services that are required. For instance, UAV-enabled caching has been proposed in vehicular networks to improve network throughput [32].

Similarly, mobile edge computing (MEC) enables consumer devices to offload and handle computationally heavy tasks that exceed battery capacity. However, UAV-enabled MEC is a proposed solution for stationary MEC servers. UAVs with edge servers can help offload computation from ground-based devices. thereby minimizing energy consumption and extending battery life. For example, a UAV enabled computation offloading system has been designed to minimize bandwidth costs, energy consumption, and network latency via deep reinforcement learning [33].

1.2.4 Balancing Load

With users' increased mobility and fluctuating traffic demands, base station traffic loads are subject to temporal and spatial variability. This variability can lead to some base stations being underutilized while others become overloaded, resulting in poor QoS[34]. While small cells can help reduce traffic imbalance, their static nature prevents them from responding effectively to sudden traffic surges. UAV-BSs offer a solution by being rapidly deployable to areas experiencing high traffic demand, thus ensuring balanced load distribution across base stations.[35].

The authors of [36] suggested a learning-based appraoch to deploy UAVs to congested network areas during peak traffic times, aiming to assist in load balancing and prevent a deterioration in user QoS. This approach allows for proactive UAV deployment by utilizing both the extreme gradient boosting (XGBOOST) algorithm and the auto-regressive integrated moving average (ARIMA) model to predict future high-traffic zones based on previous data. [37] discusses UAV deployment to facilitate load balancing and reduce the amount of communication delay that occurs between IoT devices and macro base stations (MBSs) when the MBS is experiencing a high traffic. To decide where UAVs should be deployed and how IoT devices should be associated, heuristic algorithms were created. Similarly, the study in [38] investigated the use of UAV base stations for load balancing and enhancing capacity in areas experiencing high traffic by designing efficient UAV trajectories. To achieve a high spectral efficiency, a deep reinforcement learning framework was presented for determining ideal UAV trajectories, efficiently balancing the load across UAV-BSs.

1.2.5 Extension of Coverage and Relaying

The rapid expansion of mobile devices has led to a substantial increase in demand for high-speed wireless connectivity, placing pressure on the capacity and coverage of present cellular networks. UAVs have been used to expand network capacity and offer more flexible coverage in order to overcome this problem [22]. Because of their strong LoS link, UAVs can improve wireless communication performance by reducing propagation loss and enhancing link QoS. UAVs may expand network capacity and coverage by acting as airborne base stations or relays

[39]. UAVs, for instance, aren used as a wireless-powered communication networks (WPCNs) to help send data from sources to locations with blocked communication lines [40]. These sources don't have their own energy source and have low power. The UAV functions as a hybrid access point (AP), serving as a link for data transmission and reception in addition to offering wireless power transfer (WPT) to recharge user devices.

The dominant LoS and AtG link greatly improves UAV-enabled wireless communications' efficiency [41], which leads to a low propagation losses and improved QoS. UAVs are therefore widely used as aerial base stations (BSs) or relays to expand network capacity or offer wider coverage options [42, 43, 44]. Similarly, in [45], the authors investigated that by using non-orthogonal multiple access (NOMA) technology to enhance the coverage of an existing network, UAVs can be used as relays to serve customers at the edge of the cell, hence improving QoS.

1.2.6 Improvement in Throughput and Capacity

The exponential rise in information technology and telecommunications has resulted in a notable rise in customer requirements for data traffic. Both small and macro base stations are set deployed to supply coverage in order to meet this demand. However, the continuous fluctuation in data traffic renders terrestrial small base stations alone insufficient. UAVs present a flexible and adaptable solution, offering reliable coverage and enhancing network capacity. For instance, UAVs have been deployed in heterogeneous networks to optimize capacity by determining the most effective geographic locations for deployment [46, 47].

In [48], the authors analyzed the most effective way to deploy UAVs in heterogeneous networks with the objective to increase network capacity. To identify the best locations for UAV deployment, a tility function was developed that reflects traffic intensity across different network regions, followed by the development of a heuristic method to efficiently position UAVs. The proposed model demonstrated improved capacity, reliability, significantly improved connection when compared to normal ground-based wireless networks. Similarly, a study in [49] consider deploying numerous UAVs to collect traffic from a congested terrestrial base stations, with the purpose of increasing bandwidth for ground users at the cell edge.

1.2.7 Backhauling

In mobile networks, a backhaul is responsible for connecting base stations to the core network, typically using fiber cables or microwave links. In an emergency with destroyed backhaul infrastructure, UAVs can establish ad-hoc backhaul connections. UAVs can be used for backhauling in high-mobility environments, like high-speed trains, where they enhance coverage probability by stabilizing the connection[51, 52]. In this regard, [53] presented a backhaul system that combines UAVs with free-space optical (FSO) communications with the goal of improving the coverage and efficiency of the high-speed rail network.

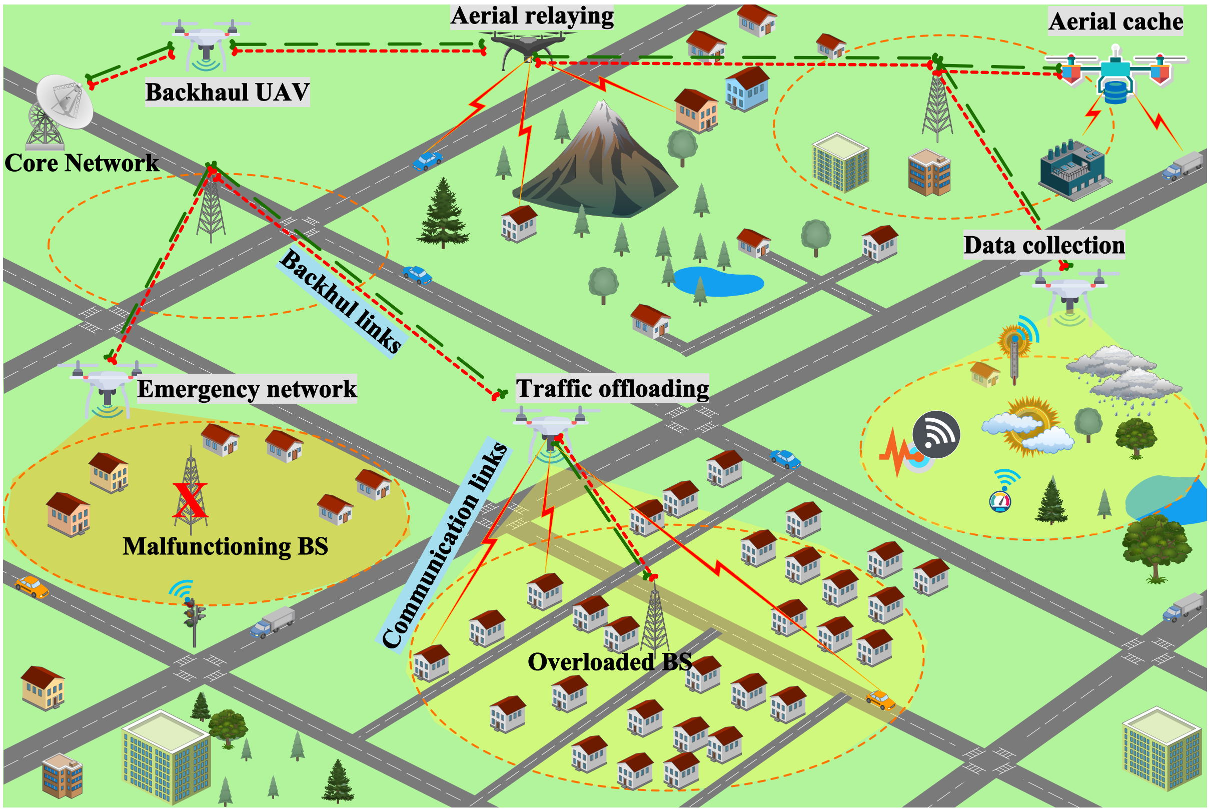

Figure 1.2: UAVs serve various roles, including providing wireless backhaul in remote areas, restoring networks during outages, extending coverage over obstacles, offloading traffic from crowded base stations, caching popular content, and harvesting data from ground sensors [50].

1.2.8 Energy Efficiency

UAVs also help cellular networks operate more efficiently in increasing their energy efficiency (EE) by assisting in capacity enhancement while minimizing power consumption. For example, in a heterogeneous network, deploying Mmwave UAVs next to macro and small base stations can increase user throughput at the cell edge thereby enhancing overall network EE. In [54], the researchers demonstrated this through integrating mmWave UAV with MBS and SBS to increase user throughput in a three-tier hybrid network at the cell edge, which thus produced an extensive improvement in the network's EE. Additionally, UAV-assisted base station sleeping strategies, where traffic is offloaded to UAVs while lightly loaded base stations enter sleep mode, have been demonstrated to considerably lower cellular network energy usage [55].

1.3 Problem Description

UAVs are becoming a revolutionary technology in the field of wireless communication networks, offering flexible deployment options, extensive coverage, and access to wide bandwidths. However, integrating UAVs into existing wireless communication infrastructures presents significant challenges. These challenges include optimizing deployment strategies, ensuring reliable and efficient communication, minimizing latency, and mitigating potential blockages caused by environmental factors or physical obstructions.

UAV-assisted communication systems are dynamic and complex in nature, especially in the context of next-generation networks like 5G and beyond, demands innovative solutions. Traditional methods for managing communication networks may not fully address the need for real-time responsiveness and precision in UAV operations. Therefore, this research aims to explore and develop advanced techniques that enhance network performance, reduce latency, predict and mitigate blockages, and improve beamforming accuracy through the integration of vision-based and machine learning approaches.

Specifically, this research will investigate how the integration of real-time computer vision with UAV networks impacts latency and overall communication performance. By addressing these challenges, the study seeks to maximize the prospective of UAVs in wireless communication, leading to more reliable, efficient, and latency-aware communication solutions.

1.4 Aims and Objectives

This thesis investigates the applications of UAV in wireless communication systems to enhance flexibility, coverage, and bandwidth efficiency while ensuring cost-effectiveness. The specific objectives are:

1. **To Explore UAV Integration with Existing Networks**: This involves investigating how UAVs can augment current wireless communication frameworks, improving efficiency and coverage.

2. **To Develop Vision-Assisted Beam Prediction**:We aim to develop a beam prediction method that utilizes machine learning and computer vision to determine optimal beam directions for UAV-based communication in 5G and beyond.

3. **To Implement Proactive Blockage Prediction**: The objective is to integrate UAVs with vision-based technologies to create a proactive blockage prediction mechanism for handover processes in future wireless networks. This approach aims to boost signal strength and ensure seamless connectivity.

4. **To Enhance Latency-Aware Vision-Aided Wireless Network**: Investigating the potential for integrating vision-based technology with UAV networks to analyze how real-time computer vision impacts the latency and overall communication performance in UAV-assisted networks.

1.5 Contributions

Using the above outlined goals as a guide, this study aims to develop novel UAV-assisted frameworks and lightweight models designed to enhance beam management, blockage prediction, and overall network efficiency in future-generation wireless systems. Through the integration of computer vision and machine learning techniques, this work addresses the critical challenges in maintaining reliable communication in high-mobility and obstacle-prone environments. The main contributions of this thesis are listed below:

- **Development of a Novel Beam Management Technique for UAV-Assisted Networks:** This dissertation introduces a novel beam management technique adapted for mmWave 5G and beyond networks. By integrating computer vision (CV) with ensemble learning, the technique utilizes the YOLO-v5 model for accurate detection and positioning of UAVs, enhancing signal-to-noise ratio and beamforming accuracy. Two neural networks are trained for optimal K-beam predictions, achieving approximately 90% top-1 accuracy. This contribution demonstrates significant improvements in signal strength for high-mobility scenarios and has been critical in advancing the field of dynamic beam management in UAV-assisted networks.

- **Proactive Blockage Prediction and Handover Management Framework for mmWave Communications:**

  A new framework for proactive blockage prediction and management in UAV-assisted mmWave networks is presented. By leveraging computer vision to detect environmental blockages and track user movement, this approach assists proactive handovers (PHO) to maintain uninterrupted line-of-sight (LOS) connectivity. The proposed solution achieves a 20% improvement in network performance, particularly in maintaining robust connections in high-mobility environments. This contribution marks a significant advancement by using UAVs for improving the reliability and efficiency of mmWave communications.

- **Lightweight Vision-Aided Machine Learning Model for UAV Beam Prediction in mmWave Technologies:**

  An advanced machine learning approach is proposed to efficiently and accurately predict optimal beam orientations for UAVs using mmWave and terahertz (THz) technologies. By utilizing real-time visual data from UAV cameras and performing on-device inference, this method achieves approximately 90% accuracy in predicting the best beam direction for the top-1, and nearly 100% accuracy for the top-3. On-device processing reduces communication delays by 15% and lowers energy consumption by 50%, demonstrating extensive improvements in real-time UAV communication efficiency.

1.6 Thesis Outline

Below is a brief outline of the structure of the subsequent sections of this thesis:

Chapter 2 offers an extensive review of the relevant literature related to Wireless Communication Networks. It covers various aspects like the integration of UAV in Communication Networks, the role of UAVs in Communication Infrastructure, previous research and practical applications in this domain, the importance of Vision-Assisted Beam Prediction, its relevance in the context of 5G and beyond UAV Communication, and the collaborative integration of UAVs and Computer Vision for Blockage Prediction. Chapter 3 is dedicated to the practical implementation of Vision-Assisted Beam Prediction in 6G UAV Communication. This chapter focuses on the methodology and techniques involved in this process. It presents the experimental setup, data collection process, and the results obtained from real-world scenarios. Additionally, the chapter discusses the implications of vision-assisted beam prediction in enhancing communication reliability and efficiency for UAV networks. It compares this approach with existing methods and suggests potential future directions. In Chapter 4, we delve into proactive blockage prediction techniques designed specifically for UAV-assisted handover in future wireless networks. We examine the difficulties that arise in predicting blockages in UAV communication scenarios and explore proactive methods for reducing the risk of communication handover disruptions. Our findings emphasize the effectiveness of proactive blockage prediction in ensuring seamless UAV-assisted handover in future wireless networks.

Chapter 5 of this thesis, focuses on the differences in latency for communication systems assisted by UAV. It compares the effectiveness of two approaches - onboard and on-ground training methods. The chapter investigates the effect of various methods on communication efficiency by looking at the latency implications of training machine learning models onboard UAVs versus on the ground. It offers an in-depth evaluation of the latency characteristics, taking into account various factors such as computation complexity and data transmission delays. Chapter 6 wraps up the thesis by summarizing the significant contributions achieved throughout the course of the research. It highlights the main findings, insights, and advancements achieved in research on communication networks assisted by UAVs. Furthermore, it provides recommendations for future research directions to further enhance the understanding and practical implementation of UAV-assisted communication technologies.

Chapter 2

Background and Literature Review

As technology continues to evolve and our reliance on wireless communication grows, several significant challenges have arisen that make it harder to maintain effective and reliable networks. Issues like the limited availability of radio frequencies [56], interference from other devices [57], and concerns about security and energy efficiency [58] are becoming more prominent. Additionally, problems such as high latency [59], maintaining connectivity while moving [60], and handling increasing amounts of data [61] put additional strain on current systems. To address these problems, innovative solutions are needed. One such solution is the use of UAVs, which can offer flexible and efficient ways to improve wireless communication by enhancing coverage, managing spectrum use, and reducing interference. The ability to widely use UAVs, including tiny planes, balloons, and airplanes, for wireless communication has been made possible by recent advancements in UAV technology [62]. UAVs, in For instance, when properly configured and managed, offer reliable and affordable wireless communication services for a range of practical applications. UAVs, on the one hand, can serve as airborne base stations (BSs), providing reliable and cost-effective, and on-demand wireless access to specific places. On the other hand, it can interact with ground users as aerial user equipment (UE), also known as cellular-connected UAVs [22].

When used as flying base stations, UAVs can connect to existing terrestrial wireless networks such as cellular and broadband networks. UAVs have several advantages over typical terrestrial base stations, including the ability to adjust altitude, avoid obstructions, and establish line-of-sight (LoS) communication links with ground users. Indeed, because of their inherent characteristics such as mobility, agility, and flexible altitude, UAV base stations may efficiently enhance present cellular networks by providing additional bandwidth to hotspot areas and providing network coverage in difficult-to-reach areas [63]. According to [22], UAVs are also useful in Internet of Things (IoT) scenarios [64, 65], where devices often have little transmitting power and are unable to connect over long distances. UAVs may also be used as wireless relays to improve the connection and coverage of ground wireless devices, as well as for surveillance situations, which is a crucial IoT use case.

In situations where there are unusual crowd gatherings, at events like music concerts, sports

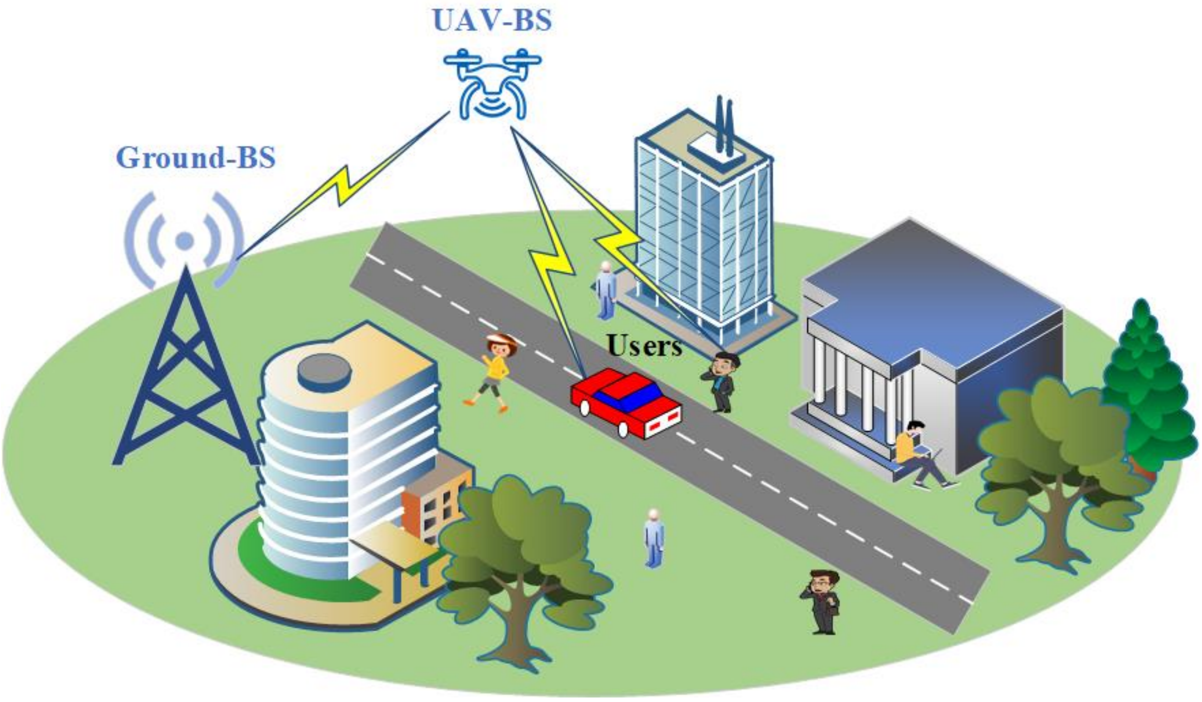

Figure 2.1: UAV-BS Communication with Ground Users.

games, or fairs, crowds often gather around a central hotspot or event area. This poses major challenges for the current cellular network infrastructure, which is generally not built to handle such rare, high-density events. Even beyond these special events, base stations (BSs) experience spatio-temporal fluctuations in traffic loads. For any given BS, the traffic load fluctuates dynamically throughout the day and across different days of the week, as highlighted in previous studies [66, 67, 68]. This leads to an interesting pattern: peak hours are often confined to specific time frames, indicating that BSs are not always running at full capacity.

Inspired by the insights from [22], a comparison between fixed BSs and UAV BSs is presented in Table 5.2.

Table 2.1: A Comparison between Fixed BS and UAV-BS

UAV Base Station	**Fixed Base Stations**
Deployment is always three-dimensional.	Two dimensional deployment
Deployment last for a short time and change often.	There are mostly long-term, fixed deployments.
UAV-BS are often deployed in unrestricted areas.	Deployed in specific places.
Mobile, Flexible and Portable in nature.	Immovable and fixed in nature.

The upcoming content will delve into the current challenges faced in wireless communication, such as spectrum scarcity, interference, security issues, and energy efficiency. It will then explore how UAV networks offer a promising solution by improving network flexibility, coverage, and performance. The discussion will also cover design considerations for UAV networks and introduce advanced techniques like vision-assisted beam prediction, highlighting their potential to address the complex issues in modern wireless communication.

2.1 Current Challenges in Wireless Communication

Wireless communication is facing several major issues as technology and demand evolve. Here are some of the current challenges:

2.1.1 Spectrum Scarcity

A limited resource is the radio frequency spectrum, and with the rise in wireless devices, the demand for spectrum has surged. Allocating enough bandwidth to different services while avoiding interference is a significant challenge [69, 70].

2.1.2 Interference and Noise

Interference from other devices, whether intentional or unintentional, can degrade signal quality. Additionally, noise from electronic devices and environmental factors can impact communication reliability [71, 72].

2.1.3 Security Concerns

Compared to wired networks, wireless networks are typically more susceptible to security breaches. Ensuring data integrity, confidentiality, and proper authentication is critical, especially with the increasing number of IoT devices [73, 74].

2.1.4 Energy Efficiency

Many wireless devices, like cellular phones and IoT sensors, rely on battery power. Improving energy efficiency to extend battery life while maintaining performance is an ongoing challenge [75, 76].

2.1.5 Latency

Low latency is crucial for applications like online gaming, virtual reality, and autonomous vehicles. Achieving ultra-low latency communication requires advanced technologies and efficient protocols [77, 78].

2.1.6 Mobility and Coverage

Maintaining a seamless connection and consistent performance while users are on the move, particularly at high speeds or across various network areas, remains a technical challenge [79, 80].

2.1.7 Capacity and Throughput

The need for high-speed data and the growing number of connected gadgets, ensuring sufficient network capacity and high throughput is essential. This involves optimizing network infrastructure and utilizing technologies like MIMO (Multiple Input Multiple Output) and beamforming [81].

2.1.8 Scalability

As the quantity of connected gadgets increases, networks must scale efficiently. This includes managing increased signaling overhead and ensuring robust performance under high load conditions [82].

2.1.9 Infrastructure Deployment

Deploying infrastructure for new technologies like 5G requires significant investment and planning. This includes installing new base stations, upgrading existing ones, and ensuring backhaul connectivity [83].

2.1.10 Environmental Impact

The deployment and operation of wireless networks have environmental implications, such as energy consumption and electronic waste. Developing sustainable practices and technologies is increasingly important [84, 85].

2.2 UAVs as a Promising Solution

One promising solution to these challenges is the deployment of UAV (Unmanned Aerial Vehicle) networks. UAV networks offer flexibility in establishing temporary communication links, especially in remote or disaster-affected areas where traditional infrastructure may be lacking or damaged. They can provide on-demand network coverage and capacity enhancement, improving mobility and coverage issues. UAVs can be quickly deployed and repositioned to offer coverage in areas where it is most required, making them particularly useful in emergency situations where rapid response is critical [86, 87].

In addition to their flexibility, UAVs can optimize spectrum usage and mitigate interference by dynamically adjusting their positions and operating frequencies. This dynamic adaptability allows UAV networks to avoid congested frequencies and minimize interference, leading to more reliable communication. By leveraging advanced algorithms and real-time data, UAVs can continuously monitor and adapt to the spectrum environment, ensuring efficient use of available resources. This capability is particularly valuable in urban environments where spectrum congestion is a significant challenge [88, 89, 90].

Furthermore, UAV networks can improve the overall robustness and efficiency of wireless communication by acting as relays or intermediate nodes, thus extending the range and coverage of ground-based networks. This can be especially beneficial in enhancing connectivity in rural or underserved areas. Incorporating UAVs into the current terrestrial networks can also improve data throughput and reduce latency by offloading traffic and optimizing routing paths. Overall, the deployment of UAV networks represents a versatile and innovative approach to addressing the multifaceted challenges facing wireless communication today [87, 90].

2.2.1 Design Considerations for UAV Networks

Designing UAV networks involves various critical considerations to ensure their effectiveness. **Communication reliability** is crucial, necessitating the implementation of robust protocols to manage signal loss and interference [91]. **Scalability** is also important, requiring architectures that can efficiently handle large numbers of UAVs and adapt to dynamic network conditions [92]. **Energy efficiency** plays a significant role, as UAVs are typically battery-powered; thus, optimizing energy consumption through efficient routing algorithms is essential [93]. Additionally, minimizing latency and ensuring real-time data processing are key to supporting applications that demand immediate response [94]. Other important design considerations include **security and privacy,** which can be enhanced through strong encryption and authentication mechanisms [86]. **Interference management** is vital, and dynamic frequency selection techniques can help mitigate disruptions [95]. **Autonomous operation and coordination** must be supported by sophisticated algorithms to avoid collisions and optimize flight paths [96]. **Regulatory compliance** is necessary to adhere to local laws and airspace rules [97], while minimizing environmental impact through sustainable practices and noise reduction is also essential [98].

2.2.2 Vision-Assisted Beam Prediction

Vision-assisted beam prediction represents a significant advancement in managing UAV networks by improving communication reliability [99, 100]. By leveraging visual data, UAVs can accurately predict and adjust beam directions, ensuring stable and high-quality communication links. This technology enhances the ability to maintain a focused connection, reducing signal loss and improving overall network performance. Real-time adjustments based on visual inputs enable UAVs to dynamically adapt to changing conditions, which is crucial for maintaining reliable connectivity in various environments. In addition to improving communication reliability, vision-assisted beam prediction enhances energy efficiency and reduces interference. Precise beam targeting minimizes the need for broad-spectrum transmission, conserving battery life and extending operational range [101, 102]. This approach also helps manage interference by adjusting beams to avoid overlapping frequencies with other communication systems. Overall, integrating vision-assisted beam prediction into UAV networks leads to more effective and adaptive operations, supporting scalability, real-time processing, and regulatory compliance while minimizing environmental impact [100, 103].

2.2.3 Approaches for Vision-Assisted Beam Prediction in UAVs

Hur et al. [99] proposed a design framework introducing a hierarchical, tree-structured codebook for adaptive beamforming that efficiently adjusts beam width and steering direction. This framework uses a three-level codebook with different subarray sizes to control beam widthlevel 1 with 32 subarrays, level 2 with 8, and level 3 with 1 subarray. The top-level codebook (W1) achieves a broad beam with a power gain of 5.09 dB, while the bottom-level codebook (W3) provides a narrow beam with a power gain of 15.05 dB. The framework uses squinting subarrays and spectral windowing to handle beam directional and gain fluctuations, with windowing applied to smooth overlapping beams. Simulation results using a 32-element array and a K-factor of 10 dB in an urban street channel model show that the multilevel codebooks joint search method provides a beamforming gain (GBF) significantly higher than the one-sided search method, which uses a steered narrow beam codebook. Specifically, the exhaustive search method achieves the highest gain but with a complexity of 4096 training steps and 6 bits of feedback. In contrast, the proposed joint search method, with 48 training steps and 6 bits of feedback, demonstrates a substantial gain improvement over the one-sided search method, which also requires 48 training steps but with slightly less feedback (5 bits). This confirms that the proposed framework effectively balances performance and complexity, achieving high beamforming gains with reduced training overhead.

AlKhateeb et al. [101] evaluated hybrid precoding and channel estimation methods through simulations in both point-to-point and mmWave cellular scenarios. In the point to point setup, the system features a BS with 64 antennas and 10 RF chains, and a mobile station (MS) with 32 antennas and 6 RF chains. Using a channel model with three paths and uniform AoAs/AoDs, the simulations show that the proposed algorithms achieve near-optimal spectral efficiency with significantly fewer iterations compared to exhaustive search methods. For instance, with 96 training steps, the performance degradation is minimal compared to exhaustive search, demonstrating the efficiency of the proposed algorithms. In a mmWave cellular setting with out-of-cell interference, the results highlight the robustness of the proposed hybrid precoding algorithm. Despite interference and lowcomplexity algorithms, the system maintains good performance, achieving reasonable gains in spectral efficiency and coverage probability. The simulations indicate that the proposed algorithms effectively manage inter-stream interference and RF hardware constraints, with minimal performance loss even with limited quantization bits. This demonstrates the practicality and effectiveness of the algorithms in real-world mmWave cellular networks.

In [103], a new three-dimensional (3D) beam training technique for UAV-assisted mmWave communications is introduced. This method uses the inverse discrete-space Fourier transform to create a flat-topped training beam. Additionally, the hybrid beamforming (BF) system is incorporated, utilizing the greedy geometric (GG) approach to determine the optimal beam. While these traditional approaches have been effective in reducing beam training overhead, the reduction is limited to one order of magnitude, which remains insufficient for handling multi-user scenarios involving high mobility.

Morais et al. [102] addresses the challenge of beam selection in mmWave communications by predicting the optimal beam based on real-time position information, rather than relying on explicit channel knowledge. The goal is to select the beam that maximizes received power $P = E[|y|^2]$. The paper introduces three machine learning approaches for beam prediction: a Lookup Table (LT), K-Nearest Neighbors (KNN), and a Neural Network (NN). The LT approach maps positions to cells in a grid and assigns beams based on the mode of reported beams within each cell. KNN estimates the best beam based on the most frequent beam among the nearest neighbors. The NN approach uses a fully connected network to learn the complex relationship between position and beam. Experimental results using the DeepSense dataset show that while LT and KNN provide reasonable performance, the NN consistently outperforms them in terms of accuracy and generalization, demonstrating its effectiveness for real-world beam prediction tasks.

Charan et al. [100] presents a multi-modal beam prediction approach for mmWave communications that integrates visual and positional data to enhance beam selection accuracy. The solution addresses the high training overhead of traditional beamforming by transforming the beam prediction into a classification task, where a beam index is assigned based on the users location in a visual scene. The proposed method leverages advances in object detection and GPS positioning to derive user location from images and position data. Three machine learning models are introduced: (i) a vision based model using a fine-tuned ResNet-50 for image data, (ii) a position-based model using a Multi-Layer Perceptron (MLP) for GPS coordinates, and (iii) a multi-modal model that combines both visual and positional inputs. The multi-modal model demonstrates superior performance, achieving over 75% top-1 accuracy and nearly 100% top-3 accuracy, compared to vision-only and position-only approaches. The proposed solution is tested using a real-world multi-modal dataset, showing that integrating visual and positional data significantly improves beam prediction accuracy, making it a promising approach for mmWave/THz communication systems.

Jiang et al. [104] investigates the use of LiDAR data for beam management in mmWave and

THz communications, focusing on beam prediction and tracking. The motivation is to address the high beam training overhead associated with narrow beam adjustments required for efficient communication in these frequency bands. By leveraging LiDAR sensory data, the paper aims to reduce this overhead and improve beam management. The proposed solution integrates a machine learning model that processes sequences of LiDAR images to predict the most promising beams. This model uses Recurrent Neural Networks (RNNs), specifically Gated Recurrent Units (GRUs), for sequential feature extraction and classification. The system can either select the top beam directly or refine it through over-the-air beam training. Experimental evaluations using the DeepSense 6G dataset show that the LiDAR-based approach achieves high accuracy in beam prediction and tracking with a top-5 accuracy of 95.6%, while significantly reducing beam training overhead compared to baseline methods. This demonstrates the potential of LiDAR data to enhance beam management in dynamic communication environments.

Demirhan et al. [105] introduces and validates radar-aided mmWave beam prediction approaches using real-world datasets for the first time. The proposed methods, leveraging deep neural networks and radar domain knowledge, significantly enhance prediction accuracy while reducing computational complexity. Evaluations with the DeepSense 6G dataset, which integrates radar and mmWave beam training data, reveal that the deep learning-based solution achieves a top-1 beam prediction accuracy of 45%, outperforming the 33% accuracy of the baseline look-up table approach. Additionally, deep learning methods reach approximately 80% top-3 and 93.5% top-5 prediction accuracy, compared to the baselines 56% and 63%. Among the radar pre-processing techniques, range-angle maps with 4-point angular FFT processing offer a notable balance, achieving a 92% top-5 accuracy with just 15 ms of pre-processing and inference time. These findings demonstrate the practical advantages of radar-aided prediction for high-mobility mmWave and sub-THz communication. Khan et al. [106] perfored a study that shows that the Vision-aided Federated Wireless Network (VFWN) approach for beam blockage prediction is highly effective in maintaining seamless connectivity in high-frequency communications. By using a distributed learning approach, the study trained a convolutional neural network (CNN) with decentralized data, enabling proactive beam blockage prediction using vision and wireless sensing data (RGB images and mmWave beams). This method shares model parameters with a centralized server instead of raw data, ensuring privacy, on-device inference, low communication costs, and collaborative intelligence. When compared to a centralized model training approach using a publicly available synthetic dataset, the proposed scheme achieved an accuracy of approximately 98.5%, closely matching the 99% accuracy of the centralized approach. This demonstrates the effectiveness of federated learning (FL) in achieving similar accuracy levels without data sharing. Additionally, the proposed technique showed an 81.31% reduction in communication costs and a 6.77% reduction in latency, highlighting significant improvements in energy efficiency and overall performance. The study suggests future research directions, including proactive handover and extending the framework to support multiple users in more complex environments.

Skondras et al. [107] presents a novel clustering and selection algorithm for Flying Ad Hoc Networks (FANETs) in fifth-generation (5G) UAV-aided networks, combined with an efficient Group Handover (GHO) scheme. The proposed algorithm elects a Cluster Head (CH) for each cluster of UAVss, which manages the mobility and handover processes within the cluster. This involves orchestrating handover initiation, network selection, and handover execution, ensuring that all cluster members are informed and can establish new communication channels. The algorithms efficiency is evaluated through extensive simulations and a real-world testbed, demonstrating its superiority over existing handover algorithms. The real-world evaluation of the proposed GHO scheme utilized a controlled laboratory testbed, integrating TP-Link Omada Cloud SDN platform components and a Huawei RH2288H V3 rack server for cloud infrastructure. The testbed included TPLINK EAP225 MU-MIMO outdoor PoAs, VMs supporting video streaming services, and up to five Pixhawk Raspberry Pi UAVs. Experimental results showed that the proposed enhanced Cluster-Based Routing in Software Defined Networking (eCBRSDN) scheme significantly reduced the average number of CH elections compared to the original CBRSDN scheme. Specifically, the eCBRSDN elected an average of three CHs per PoA, while the original CBRSDN elected eight, highlighting the proposed schemes reduced overhead and improved efficiency in managing UAV mobility and communication.

2.2.4 Overview of UAVs in Communication Infrastructure

Collaborative UAV Networks

Collaborative UAVs are specifically designed to work together towards a common goal, such as generating high-resolution images for disaster relief or monitoring agriculture. By collaborating, these UAVs can perform tasks like trajectory formation, cooperative localization, and data collection, which are essential for urban and smart city applications. However, there are several challenges in these networks, including communication, control, and cooperation among UAVs. To overcome these challenges, advanced collaborative communication mechanisms and control strategies are necessary to ensure efficient operation and mission completion [108].

UAV Communication Channels

UAVs communication, especially in UAV-to-UAV links, relies mainly on Line-of-Sight (LoS) conditions. This means that direct connectivity is highly important and the impact of multipath fading is minimal. This situation suggests the use of mmWave communications for high-capacity UAV-UAV backhaul links. However, the high Doppler shift associated with UAV mobility and mmWave frequencies can be a challenge [5].

5G-and-Beyond Networks with UAVs

Integrating UAVs into 5G-and-beyond networks presents opportunities to overcome signal blockages caused by obstacles such as high-rise buildings, using intelligent repositioning of UAV-based stations (UAV-BSs). This integration also enables wider coverage for IoT and sensor networks by using UAVs as mobile data collectors, which minimizes energy consumption while maximizing connectivity [109].

2.3 Handover Management in UAV Networks

Handover (HO) is a crucial process in wireless communication systems that ensures uninterrupted connectivity for mobile users by transitioning their connection from one cell to another while maintaining QoS. This process is necessary in various scenarios, such as when a user moves between cells, experiences poor signal quality, or when load balancing between cells is required [110]. The primary goals of HO include maintaining strong signals, balancing the network load, improving throughput, reducing radio link failures, minimizing interruptions, and lowering energy consumption.

HO management presents significant challenges in 5G networks, primarily because of the common and often random placement of small cells and will also be a critical issue in 6G networks, which are expected to be highly dynamic, multi-layered, and expansive. Most HO algorithms utilized in 4G networks are ineffective for 5G due to the differing requirements of 5G networks. Therefore, a thorough reassessment of existing algorithms is necessary to achieve optimal HO performance. High packet error rates, load balancing requirements, and serving signal loss are some of the factors that could trigger HO, necessitating a switch to a different network if any of these factors reaches to unfavorable levels [111].

The handover process is divided into three key stages: detection, decision, and execution. During the detection phase, the system continuously observes the quality and strength of the present cell's signal as well as those of nearby cells. In the decision-making phase, the system assesses neighboring cells to identify the best target based on signal quality. Finally, in the execution phase, the handover procedure is initiated [112]. Figure 2.2 presents a visual overview of the HO management procedure. Vision-assisted beam prediction significantly advances handover management in UAV networks by enhancing communication reliability and efficiency. This technology leverages visual data to predict and adjust beam directions, ensuring stable connections and reducing signal loss. Real-time visual input allows UAVs to dynamically adapt to changing conditions, crucial for maintaining reliable connectivity in various environments. By minimizing broad-spectrum transmissions and precisely targeting beams, energy efficiency is improved, and interference is reduced. Additionally, integrating machine learning models for beam prediction based on positional and visual data further enhances the accuracy and adaptability of UAV communications. The implementation of hierarchical codebooks and hybrid

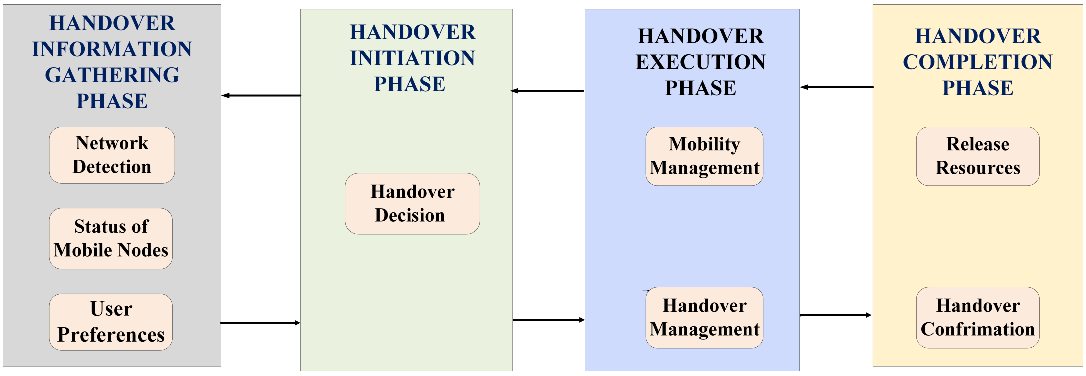

Figure 2.2: Handover Management Process.

precoding techniques in beamforming optimizes performance while reducing complexity and training overhead. These advancements in vision-assisted beam prediction not only enhance network performance but also facilitate scalability, real-time processing, and regulatory compliance necessary for effective handover management in UAV networks.

2.3.1 Factors effecting Handover in 5G and Beyond

This section outlines the critical factors that affect HO's performance and requirements in 5G and 6G networks [111]. Although 6G is expected to deliver lower latency, it will also introduce challenges such as higher operating frequencies, a greater density of connected users, and more latency-sensitive applications, all combined with increased mobility. These changes will require more frequent and faster HOs between cells. To maintain a smooth user experience in 6G, the development of advanced HO management strategies will be critical [113].

1. **Operating Frequency:**
   (a) **5G:** Operates at 700 MHz and Sub-6 GHz frequencies.
   (b) **6G:** Operates at 26, 28 GHz, and frequencies above 100 GHz.
   (c) **Relationship with HO:** The challenges associated with HO increase as the operating frequency rises.
2. **Connection Densification:**
   (a) **5G:** Supports a density of 10^6 devices per square kilometer.
   (b) **6G:** Expected to support a density of 10^7 devices per square kilometer.
   (c) **Relationship with HO:** As the density of devices in an area increases, the complexity of handling HO likewise escalates.
3. **Latency Sensitivity:**
   (a) **5G:** Latency is around 1 millisecond.

   (b) **6G:** Latency is expected to be less than 1 millisecond.

   (c) **Relationship with HO:** Faster HO processes are necessary in 6G networks to meet the lower latency requirements.

4. **High-Speed Mobility:**

   (a) **5G:** Capable of supporting mobility speeds of up to 500 km/h.

   (b) **6G:** Expected to support mobility speeds of up to 1000 km/h.

   (c) **Relationship with HO:** As mobility speed increases, the demand for quicker and more efficient HO also increases.

2.3.2 Handover types

Hard Handover (Break-Before-Make)

In hard handover, the connection to the current cell is fully terminated before a new connection is made with the target cell. This type of handover is typically used in 2G (GSM) networks where the mobile device momentarily loses connection as it switches from one cell to another. This approach is simpler and less resource-intensive but can lead to a brief service interruption. A common use case is during rapid movement, such as driving through urban areas with densely packed cell sites, where the device must frequently switch connections [114].

Soft Handover (Make-Before-Break)

In soft handover, the mobile device is allowed to maintain connections with multiple cells simultaneously during the transition period, ensuring a seamless switch without any noticeable interruption to the user. This method is widely used in 3G (UMTS) networks, where overlapping coverage areas allow for this redundancy. A typical use case is in suburban or rural areas where cell towers are further apart, and maintaining multiple connections ensures consistent service as the user moves [115].

Softer Handover

Softer handover is a variant of soft handover that takes place between different sectors within the same cell site. This is commonly found in CDMA-based systems where the transition happens within the same base station, providing a smooth switch without loss of connection. An example use case is in large public venues like stadiums or shopping malls where multiple antennas serve different sectors of the same area, ensuring continuous connectivity as users move within the venue [116].

Horizontal Handover

Horizontal handover refers to the transition between two base stations of the same network type, such as from one 4G LTE cell to another. This type of handover is crucial for maintaining service continuity in dense urban environments where users frequently move through overlapping cell coverage areas. For instance, a person walking through a city center may experience multiple horizontal handovers to maintain a stable connection as they move from one cells coverage area to another [117].

Vertical Handover

Vertical handover involves transitioning between different types of networks, such as moving from a Wi-Fi network to a 4G cellular network. This type of handover is essential for ensuring seamless connectivity when a user moves out of a Wi-Fi hotspots range and into an area covered by cellular service. A typical use case is a person leaving their home or office Wi-Fi network and continuing their online activities via the cellular network without any interruption [118].

Intra-cell Handover

Intra-cell handover occurs within the same cell but involves switching to a different channel or frequency. This type of handover is used to manage interference or load balancing within a cell. For example, if a specific frequency within a cell becomes congested or experiences interference, the network can perform an intra-cell handover to switch the user to a clearer channel, thus maintaining call quality and data throughput [119].

Inter-cell Handover

Inter-cell handover is the transition of a call or data session between different cells, ensuring continuous service as the user moves from one coverage area to another. This is the most common type of handover in mobile networks and is crucial for maintaining connectivity during movement. A typical scenario is a person driving along a highway, moving through various cell coverage areas, and requiring seamless transitions to avoid dropped calls or data sessions [119].

Inter-frequency Handover

Inter-frequency handover involves a change in the operating frequency during the handover process, which is necessary when moving between cells that operate on different frequencies. This type of handover is often required in heterogeneous network environments where different frequency bands are used for different coverage areas. For instance, a mobile user moving from a macro cell to a small cell may experience an inter-frequency handover to utilize the optimal frequency for each cell type [120].

Inter-system Handover

Inter-system handover occurs between different types of networks, such as transitioning from an LTE network to a 3G or 2G network. This type of handover is critical when moving out of the coverage area of a higher-generation network into an area only served by older networks. An example use case is when a user travels from a city with extensive LTE coverage into a rural area where only 3G or 2G networks are available, ensuring that the connection is maintained without interruption [121].

Forced Handover

Forced handover is initiated by the network to prevent call drops due to poor signal quality or network congestion. This type of handover is crucial for managing network resources and ensuring quality of service, especially in high-traffic areas. For instance, during a large event such as a concert or sports game, the network may perform forced handovers to distribute the load more evenly across available cells, preventing any single cell from becoming overloaded and ensuring continuous service for all users [122].

2.3.3 Handover Challenges in UAVs Network

Ensuring continuous connectivity in UAV networks is vital as UAV move across different coverage areas. The process of switching connections from one UAV BS to another poses unique challenges because of the changing nature of UAV movements. Addressing these challenges is essential for maintaining seamless communication and network reliability.

1. Characterization of Mobility Models for UAV Cellular Networks Regarding Handovers: In UAV cellular networks, handovers occur when the serving UAV base station (UBS) changes for a typical usereven static users can experience handovers. Researchers have explored various mobility models to understand displacement probability and flight duration of UAVs. The choice of mobility model significantly impacts handover probability and rate in UAV networks [123].

2. Handover Management for Connected UAVs: Effective handover management in connected UAVs is a major challenges in UAV networks. Researchers have extensively studied this area to address the difficulties associated with transitioning UAVs smoothly between base stations during flight. The primary focus is on overcoming mobility-related issues to ensure that UAVs maintain continuous and reliable connectivity as they move through various network cells [124].

In summary, handover challenges in UAV networks are critical for maintaining seamless connectivity as UAVs fly across different coverage areas. Researchers continue to explore innovative solutions to enhance handover performance and reliability.

2.3.4 Handover Procedure in UAVs

The handover process is a crucial aspect of 5G networks, involving various steps, algorithms, and techniques that enable User Equipment (UE) to transition its connection from one cell to another. The specific procedural steps can vary depending on the technology in use. While the procedures used for terrestrial UEs can be applied to UAVs, they may not ensure optimal handover performance due to the unique characteristics of UAVs. This section gives an overview of the HO process for a particular handover system scenario, as shown in Figure 2.3 [124].

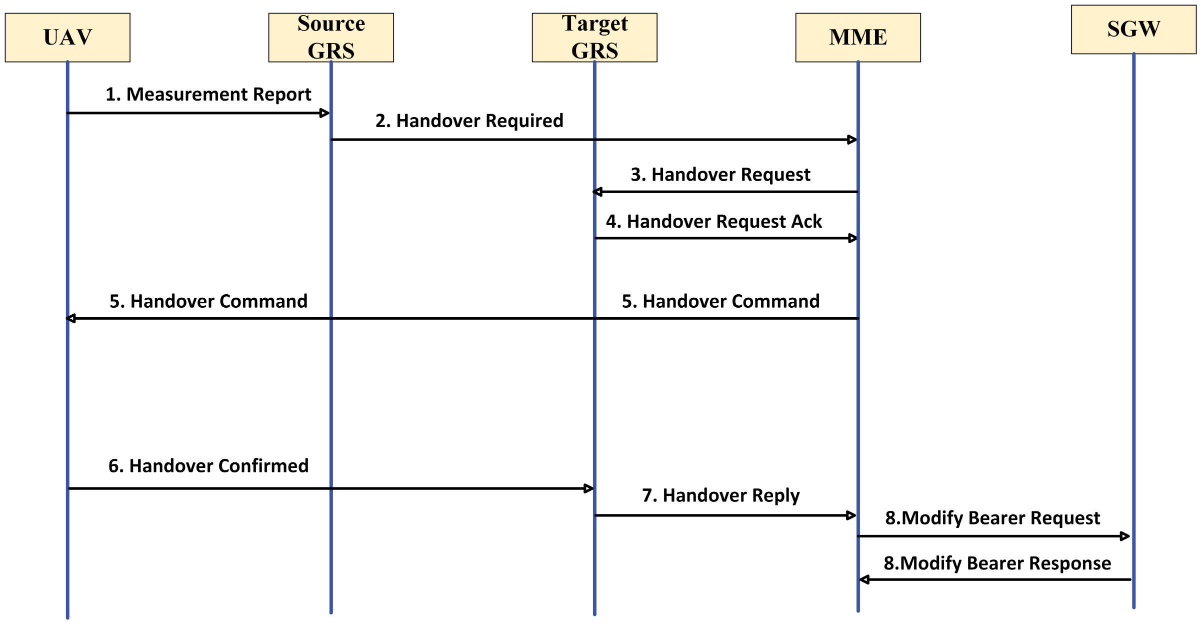

Figure 2.3: A Handover Procedure.

The Mobility Management Entity (MME) has been replaced by the Access and Mobility Management Function (AMF) in the 5G handover process, which is similar to the LTE-Advanced system with a few enhancements [124]. The User Plane Function (UPF), on the other hand, continues to serve the same role as the Serving Gateway (SGW). The HO begins with the User Equipment (UE) periodically sending measurement reports to the Source Base Station (S-BS). Following these reports, the S-BS configures the UE's measurement procedures. Once sufficient data has been gathered, the S-BS evaluates the measurements and decides if a HO is necessary. Upon making this decision, the S-BS sends a HO request to the Target Base Station (T-BS). The T-BS then assesses its resources and responds with an acknowledgment to the S-BS, indicating whether it can accommodate the handover.

The UE receives the necessary data from the Target Base Station (T-BS) to establish a connection to the target cell once the HO is initiated. The T-BS then provides the UE with uplink allocation and timing details. Later, the T-BS updates the Access and Mobility Management Function (AMF) about the UEs cell alteration, prompting the User Plane Function (UPF) to update the UEs path. Once these updates are made, the AMF informs the T-BS of the path update, and the T-BS, in turn, notifies the Source Base Station (S-BS) to complete the handover.

2.4 Handover Techniques in UAV Networks

2.4.1 Mobility Model Characterization for UAV Cellular Networks Regarding Handovers

Researchers have explored various mobility models to analyze the probability of displacement and flight duration of UAVs. Some commonly used models include:

1. **Straight Line (SL) Mobility Model:** Drawing inspiration from the simulation model used in 3GPP, this model is straightforward and widely employed due to its simplicity.

2. **Random Walk (RW):** Nodes choose random angles of movement and travel unplanned lengths between each stop.

3. **Random Waypoint (RWP):** Similar to RW but with added pause time (hovering) at each stop.

4. **Random Direction (RD):** Nodes can change their direction only at the boundaries of the environment, which helps prevent node clustering.

5. **Modified Random Direction (M-RD):** An improved version of RD that integrates intermediate stops within the nodes path, ensuring coverage across the entire environment.

The choice of mobility model significantly impacts handover probability and rate in UAV networks.

2.5 Handover Management for Connected UAVs

1. **Predictive Handover Techniques:** Predictive handover methods utilize algorithms to forecast a UAVs future position and determine the optimal time to initiate handover. These techniques improve handover efficiency by reducing latency and preventing connection drops. For instance, employing machine learning models to predict the UAVs trajectory can enhance the timing and accuracy of handovers [103].

2. **Seamless Handover Protocols:** Seamless handover protocols focus on minimizing the disruption during the handover process. Techniques such as buffering data or preestablishing connections with the target base station can reduce service interruptions. The integration of seamless handover protocols ensures that UAVs experience minimal downtime as they switch between base stations [100].

3. **Network-assisted Handover Management:** Network-assisted approaches involve the base stations and network infrastructure in the handover process. This can include coordinating handovers between base stations to ensure a smooth transition or using network

resources to support handover decisions. Such techniques leverage network intelligence to optimize the handover process [107].

4. **Hybrid Handover Strategies:** Hybrid strategies combine multiple handover techniques to address different aspects of the handover challenge. For example, combining predictive models with network-assisted protocols can enhance the robustness and efficiency of the handover process. This approach ensures that various scenarios and challenges are managed effectively [104].

2.6 Network Optimization Challenges

In UAV networks, optimizing handovers involves addressing several key challenges [125]. These include managing the Automatic Neighbouring Relation (ANR), dealing with frequent handovers, and preventing UAV disconnects. Several solutions and approaches have been proposed to tackle these issues:

1. **Automatic Neighbouring Relation (ANR):** Advanced techniques can be used to control the number of neighbors in the Neighbour Relation Table (NRT) and deal with possible deletions or block-listing. Techniques such as adaptive neighbor management and predictive caching can optimize the NRT by dynamically adjusting the list based on UAV movement patterns and historical connectivity data. To effectively manage the NRT, for example, ML algorithms can be used to predict which neighbors are likely to be relevant in the near future [126].

2. **Frequent Handovers:** To address the challenge of frequent handovers due to UAVs moving in three dimensions and traversing multiple cells, several strategies can be implemented. These include the use of predictive handover algorithms that forecast the UAVs movement and pre-emptively establish connections with upcoming base stations. Additionally, implementing hierarchical handover management schemes, where handovers are managed in tiers, can reduce the frequency and impact of handovers by grouping multiple UAVs and handling their transitions more efficiently [127].

3. **UAV Disconnects:** Ensuring that handovers do not cause UAVs to disconnect from the network requires robust handover protocols and network design. Techniques such as pre-connection establishment, where a secondary connection is set up before the handover occurs, and seamless handover protocols, which include buffering and retransmission strategies, can help mitigate disconnects. Employing network-assisted handover approaches, where base stations coordinate and assist in the handover process, can further enhance continuity and reduce the likelihood of disconnects [124].

Effective handover management in UAV networks, which involves seamlessly transitioning UAVs between base stations, can be significantly enhanced by integrating computer vision technologies.Mobility models like Random Waypoint (RWP) and Straight Line (SL) provide foundational predictions of UAV trajectories, but incorporating real-time visual data from onboard cameras can refine these models by offering environmental context and predicting blockages more accurately. Predictive handover techniques benefit from computer vision by enhancing trajectory forecasts, while seamless handover protocols are improved through better obstacle detection and avoidance. Network-assisted management and hybrid strategies also leverage computer vision to support more informed handover decisions and mitigate issues related to frequent transitions and potential UAV disconnects. Overall, integrating computer vision into handover management addresses network optimization challenges by providing detailed environmental insights, thus ensuring more reliable and efficient UAV operations.

2.7 Literature Review on UAV Connectivity and Handover Management

In the context of advancing UAV technology and its integration into existing cellular networks, a comprehensive review of the existing literature is critical. The following table 2.2 describes a summary of key studies that have explored various aspects of UAV connectivity and handover management. The reviewed literature covers a wide range of topics, including mobility management, coverage enhancement, the impact of UAV altitude on network performance, and the application of machine learning models for optimizing UAV operations. Each study is analysed with respect to its research focus, employed methodology, primary objectives, and the specific environment in which the research was conducted. This structured review serves as the foundation for identifying current trends, challenges, and gaps in the research, guiding the subsequent analysis and discussion in this dissertation.

Table 2.2: Literature Review on UAV Connectivity and Handover Management.

Ref	Research Focus	Methodology	Objective	Limitation	Future Work
[128]	Using CoMP transmission for UAV connectivity	Evaluation of static and mobile UAV-UE with clustered base stations	Enhance connectivity and coverage probability for UAV-UE	Limited empirical validation; most results are based on simulations	Conduct real-world experiments to support the proposed models and frameworks

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Table 2.2 – continued from previous page

Ref	Research Focus	Methodology	Objective	Limitation	Future Work
[129]	Mobility management for UAVs in cellular networks	Model-based and deep Q-network approaches for handover optimization	To improve service availability and minimize handovers for UAVs utilizing model-based and learning-based mobility management schemes	Dependence on simulations without real-world validation	Run real-world experiments to validate the proposed algorithms in diverse environments
[130]	Seamless connectivity challenges for UAV-UE	Simulation of UAV-UE coverage probability and handover rate for static and mobile UAVs using realistic antenna models	Analyze UAV performance under practical antenna configurations for both static and mobile UAVs	The study is based on simulations without real-world validation	Conduct real-world experiments to validate the findings in diverse environments
[131]	Integrating aerial users into cellular networks	Field trial with a commercial LTE network	To investigate how different UAV performance indicators on commercial LTE networks are affected by flying altitude	The study focuses on field experiments in specific urban areas, limiting generalizability to other environments	Conduct field testing in diverse environments to validate the findings and enhance UAV connectivity strategies

Continued on next page

Table 2.2 – continued from previous page

Ref	Research Focus	Methodology	Objective	Limitation	Future Work
[132]	Delay performance of UAVs in LTE and 5G networks	Real-world measurements of delay in suburban and urban environments	Analyze delay performance linked to SINR and handover frequency	The study is restricted to specific suburban and urban settings, which may not represent all real-world conditions	Expand testing to a wider variety of environments to increase generalizability of delay performance outcomes
[133]	UAVs as base stations and user equipment	Study of coverage probability and throughput in VHetNets	In order to assess the effectiveness of UAVs linked to cellular networks, focusing on UAV-UE and UAV-BS in vertical heterogeneous networks (VHetNets)	Limited exploration of practical deployment challenges of UAV-BSs in dense urban environments	Examine real-world deployment scenarios in urban areas, focusing on interference management and reliable connectivity
[134]	Predicting QoS for UAV communications in 5G networks	Field tests and machine learning models	Improve UAV operations through QoS prediction	Limited to suburban environments, which may not represent all UAV use cases	Expand field tests to urban and rural conditions to improve QoS predictions for various UAV operations

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Table 2.2 – continued from previous page

Ref	Research Focus	Methodology	Objective	Limitation	Future Work
[135]	Optimizing handovers using Q-learning	Evaluation of scenarios in rural, semi-rural, and urban areas	To optimize the number of handovers for UAVs using a Q-learning-based algorithm in various network environments	The study applies simulated environments (rural, semi-rural, urban) without real-world validations	Incorporate real-world analysis and expand the model to include 3D UAV mobility and multi-operator networks
[136]	UAV connectivity optimization using REQIBA	Regression and deep Q-learning for BS association	To propose an intelligent UAV-to-BS association using regression and deep Q-learning for maximizing data throughput	The study is restricted to simulated environments and lacks real-world validation of the suggested approaches	Conduct real-world experiments to support the performance of REQIBA in various environmental conditions
[137]	UAV trajectory and handover management optimization	Dueling double deep Q-network (D3QN) algorithm	To optimize UAV trajectory and handover using a D3QN algorithm	The study is limited to simulated environments, which may not fully portray real-world complications	Test in real-world network environments to validate the suggested D3QN model
[138]	Enhancing UAV communication reliability	Simulations of UAV communication in urban environments using real network and 3D models	To improve UAV communication using multi-operator diversity	Relies on simulations, lacks real-world validation	Validate with real-world UAV deliveries in urban areas

Continued on next page

Table 2.2 – continued from previous page

Ref	Research Focus	Methodology	Objective	Limitation	Future Work
[139]	Mobility and handover management in future networks	Studies current solutions for UAV mobility management and suggests enhanced handover techniques	To focus mobility and handover challenges for UAVs in ultra-dense heterogeneous networks	Depend on theoretical models and lacks real-world validation	Assess mobility solutions in real-world ultra-dense networks to validate practical applicability

2.7.1 Findings from the Literature on UAV Connectivity and Handover Management

The literature review conducted on UAV connectivity and handover management in cellular networks has revealed several critical insights and trends that are helpful in understanding the current state of research in this domain. The findings are categorized into key areas, highlighting the contributions, methodologies, and objectives of various studies.

Enhancement of UAV Connectivity and Coverage

A significant amount of research focuses on enhancing UAV connectivity and coverage within cellular networks. Methods such as Coordinated Multipoint (CoMP) transmission, realistic 3D antenna configurations, and the analysis of practical system parameters have been employed to address the unique challenges posed by UAV mobility and varying altitudes. Studies such as those by [128] and [130] highlight the importance of improving coverage probability and reducing the likelihood of handover failures as UAVs navigate through clustered base station networks and urban environments. These advancements are critical for maintaining reliable UAV operations, particularly in scenarios where uninterrupted connectivity is essential.

Mobility Management and Handover Optimization

The optimization of handovers and effective mobility management for UAVs within cellular networks are significant topics across several studies. Research employing model-based approaches, deep Q-networks, and reinforcement learning algorithms, such as [129], demonstrate the potential to reduce the frequency of handovers and improve service availability. These methodologies are particularly relevant[137] in complex network environments where UAVs need to maintain seamless connectivity while transitioning between different cells. The development of these techniques marks a significant step further in ensuring that UAVs can operate efficiently in various network conditions without compromising connectivity.

Impact of UAV Altitude on Network Performance

Another important area of interest is the effect of UAV altitude on network performance. Studies like those by [131] and [132] have conducted field tests and real-world measurements to assess how altitude influences network metrics such as delay and Signal-to-Interference-plus-Noise Ratio (SINR). The findings imply that UAV altitude plays a vital role in determining the reliability of the network and the probability of handovers. These insights are particularly valuable for the design and deployment of cellular networks intended to support UAV operations at different altitudes, as they highlight the need for altitude-aware network planning and management.

Predictive Quality of Service (QoS) Models for UAV Communications

Predictive models, particularly those leveraging machine learning, have appeared as powerful tools for predicting Quality of Service (QoS) in UAV communications. Study in [134] has demonstrated the potential of these models to improve UAV operations by predicting throughput and other critical performance indicators in 5G networks. The ability to predict QoS problems before they effect UAV performance is crucial for maintaining the reliability and efficiency of UAV missions, especially in suburban and urban settings where network conditions tend to be highly dynamic.

UAVs in Vertical Heterogeneous Networks (VHetNets) and Future Networks

The integration of UAVs into Vertical Heterogeneous Networks (VHetNets) and the exploration of future network architectures, such as 5G and beyond, are also important areas of research. Studies like [133] and [139] focus on enhancing coverage and capacity for both aerial and terrestrial users by leveraging the unique capabilities of UAVs as both user equipment and base stations. This research is critical for the future of UAV operations, as it explores how next-generation networks can support the growing need for UAV services in a variety of scenarios, from urban delivery systems to disaster recovery operations.

Trajectory Management and Environmental Considerations

Finally, the optimization of UAV trajectories and the management of environmental factors are key considerations in the research. Advanced algorithms, such as the Dueling Double Deep Q-Network (D3QN) used in [137], are employed to refine UAV trajectory management, reducing the incident of handovers and minimizing interference. This field of research is very important for UAVs that operate in dynamic situations, where factors such as building topology and weather conditions can significantly impact connectivity and operational efficiency.

2.7.2 Trends and Gaps in Current Research

The literature uncovers a clear trend towards the adoption of advanced machine learning techniques and the integration of UAVs into increasingly complex network environments. As networks evolve towards 5G and beyond, the need for sophisticated models and algorithms to manage UAV connectivity and mobility becomes more evident.

However, despite the progress made, several gaps remain. Notably, there is a need for real-time adaptive models that can dynamically respond to the rapidly changing conditions in UAV operations. Additionally, further investigation is required to explore the impact of environmental variables on UAV connectivity and how these can be mitigated through innovative network design and management strategies.

2.8 Integration of UAVs and Computer Vision for Blockage Prediction

The introduction of extremely dense networks and the rapid adoption of 5G technologies require innovative approaches to address infrastructure and environmental issues that affect connectivity. Using UAVs (UAVs) alongside with computer vision technology is one such innovative method for anticipating and reducing wireless network traffic.

The main research articles that examine this integration are compiled and summarized in this literature review table, which focuses on the potential for UAVs with computer vision capabilities to improve blockage prediction and, consequently, network reliability.

Table 2.3: Literature Review Integration of UAVs and Computer Vision for Blockage Prediction

Ref	**Objective**	**Methodology**	**Key Findings**	**Limitations**	**Future Work**
[140]	Use CV and NN to predict beam blockages and perform proactive handovers in UDNs	CV for environment awareness, NN for predicting RSS drops, introduction of BLK event for proactive handover	Accurate blockage prediction, improved handover timing, maintains seamless connectivity	Dependency on high-quality visual data, complexity in predicting moving objects	Enhance real-time processing, reduce dependency on visual data

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Table 2.3 – continued from previous page

Ref	Objective	Methodology	Key Findings	Limitations	Future Work
[141]	Develop dynamic blockage prediction solutions using CV for high-frequency wireless networks	Dynamic blockage prediction using CV, implementation in 6G wireless communication scenarios	Effective blockage prediction, timely handover facilitation	Early-stage research, needs real-world validation	Real-world testing, integration with existing 6G infrastructure
[142]	Leverage CV to enhance beam alignment and predict blockages in V2X communications	Use of CV for beam alignment, prediction of blockages in vehicle-to-everything (V2X) scenarios	Improved beam alignment accuracy, enhanced blockage prediction	Limited to V2X scenarios, high computational requirements	Expand to other wireless communication scenarios, optimize computational efficiency
[143]	Solve blockage and energy efficiency issues using RIS and federated deep learning in UAV networks	Integration of RIS with UAVs, use of federated deep learning to enhance blockage prediction and spectral efficiency	Enhanced spectral efficiency, significant improvement in blockage prediction	Initial setup complexity, dependency on RIS technology	Simplify deployment, broaden applicability to diverse environments
[144]	Address proactive blockage prediction using deep learning and fusion of wireless and vision data	Deep learning algorithms to predict blockages using wireless and vision sensory data	High accuracy in blockage prediction, improved network reliability	Requires extensive data collection, high computational resources	Develop lightweight models, test in various real-world scenarios

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Table 2.3 – continued from previous page

Ref	Objective	Methodology	Key Findings	Limitations	Future Work
[106]	Improve latency in blockage prediction for wireless networks using federated learning	Federated learning with a focus on latency reduction, use of multi-modal data including vision and wireless signals	Reduced latency, improved prediction accuracy	Complexity in federated learning implementation, need for diverse data	Enhance federated learning models, expand dataset variety
[145]	Enhance ultra-reliable low-latency (URLL) communications using computer vision	Use of CV to identify services and coexist in URLL communication environments	Improved service identification, better coexistence in dense networks	High dependency on visual data quality, computationally intensive	Optimize CV algorithms for URLL, reduce computational load
[146]	Enable proactive handover and accurate blockage prediction in indoor mmWave and THz networks	Use of RGB-depth (RGB-D) information and beam index to detect and localize users, predict their trajectory, and foresee blockages	High blockage prediction accuracy (97%), significant improvement over conventional schemes	Processing latency and power consumption due to frequent object occlusions and diversity of obstacles	Optimize processing techniques, extend to various indoor environments

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Table 2.3 – continued from previous page

Ref	Objective	Methodology	Key Findings	Limitations	Future Work
[147]	Develop computer vision-aided wireless beam prediction for mmWave UAVs	Use of RGB images and beam indices, pruning redundant filters in deep neural networks to meet ultra-low-latency requirements	Reliable performance, reduced computation cost, enhanced mmWave communication	High dependency on visual data quality, need for extensive simulation and validation	Further simulation and validation, optimize for different mmWave scenarios
[148]	Develop a dataset framework for vision-aided wireless communication research	Creation of a comprehensive dataset combining visual and wireless data for deep learning applications	Useful dataset for research, enhances the development of CV and ML solutions	Dataset may not cover all scenarios, requires continuous updates	Expand dataset to include more diverse scenarios, regular updates
[149]	Focus on predicting latency probabilities in wireless networks using data-driven approaches	Use of data-driven models to predict latency probabilities, focusing on tail probabilities in wireless communication	Enhanced latency prediction, better network performance	High data requirements, complex modeling techniques	Simplify modeling techniques, reduce data dependency
[150]	Explore the convergence of wireless communications and computer vision in beyond 5G networks	Integration of CV and wireless communication techniques to enhance network performance	Improved network performance, better integration of CV and wireless technologies	Early-stage research, needs practical validation	Practical implementation and testing, further integration development

Continued on next page

Table 2.3 – continued from previous page

Ref	Objective	Methodology	Key Findings	Limitations	Future Work
[151]	Propose a UAV-assisted ISAC system for blockage prediction and improved communication	Radar and wireless integration for sensing and communication, beamforming optimization, simulations	Improved ISAC performance, manageable trade-offs between sensing and communication	Reduced radar detection with high communication power, need for trade-off optimization	Explore machine learning for better blockage prediction and beam design, study optimal trade-offs

2.8.1 Findings from the Literature of UAV Integration with Computer Vision

The integration of UAVs and CV technologies in wireless communication systems has been increasingly studied to address issues such as blockage prediction, handover management, and network reliability. This section summarizes the key findings from the literature reviewed on this topic, highlighting both the progressions made and the existing gaps that offer opportunities for further research.

Blockage Prediction and Proactive Handover Management

Recent studies have demonstrated the potential of using computer vision and neural networks to predict beam blockages and facilitate proactive handovers in ultra-dense networks (UDNs) and next-generation wireless communication systems such as 5G and beyond. For instance, Al-Quraan et al. [140] developed a system that utilizes computer vision for environment awareness and neural networks for predicting signal strength reductions, introducing the concept of a blockage event (BLK) to initiate proactive handovers. This approach has been shown to significantly improve the timing of handovers, thus maintaining seamless connectivity. However, the effectiveness of these systems is often constrained by their dependence on high-quality visual data and the inherent complexity in accurately predicting the behaviour of moving objects.

Enhancing Beam Alignment in High-Frequency Networks

The application of computer vision in high-frequency wireless networks, particularly in mmWave and THz bands, has been another focus of research. Xu et al. [142] and Liu et al. [146] have explored the use of computer vision to enhance beam alignment and predict blockages in vehicle-to-everything (V2X) communications and indoor mmWave environments, respectively. These studies report significant improvements in blockage prediction accuracy, with Liu et al. achieving up to 97% accuracy. Despite these advancements, these methods are often limited to specific scenarios, such as V2X, and are challenged by the high computational requirements needed to process frequent object blocking and diverse obstacles.

Energy Efficiency and Spectral Management

Spectral management and Energy efficiency are critical concerns in UAV-enabled communication networks. Park et al. [143] integrated Reconfigurable Intelligent Surfaces (RIS) with UAV networks and utilized federated deep learning to improve both blockage prediction and spectral efficiency. While this integration offers enhanced performance, it also introduces complexities, particularly in the initial setup and dependency on RIS technology. These findings indicate that while UAV and CV integration can prominently improve network efficiency, there remains a need for simplified deployment processes and wider applicability to various environmental conditions.

Latency Reduction and Real-Time Processing

Latency in blockage prediction is another critical area addressed in the literature. Khan et al. [106] utilized federated learning with multi-modal data to focus on reducing latency in prediction models, which is crucial for real-time processing in dynamic wireless environments. Similarly, Mostafavi et al. [149] utilized data-driven models to predict latency probabilities in wireless networks, emphasizing the importance of managing tail probabilities to improve overall network performance. Despite their successes in reducing latency, these approaches face challenges related to the complexity of federated learning implementation and the high data requirements necessary for accurate predictions.

Dataset Development for Vision-Aided Wireless Communication

The development of comprehensive datasets that combine visual and wireless data has been acknowledged as critical for advancing research in vision-aided wireless communication. Alrabeiah et al. [148] created a dataset framework designed to support the development of computer vision and machine learning solutions for wireless communication. While this dataset is a valuable resource, it does not cover all potential scenarios, highlighting the need for continuous updates and expansions to include more diverse and challenging environments.

2.8.2 Future Research Directions

The literature identifies numerous key areas for future research. These include enhancing real-time processing capabilities, reducing the dependency on high-quality visual data, expanding the application of these technologies beyond specific scenarios such as V2X, and validating these methods in real-world environments. Additionally, there is a need for further development of lightweight models that can operate efficiently in diverse and complex environments, as well as the exploration of machine learning techniques to optimize the trade-offs between sensing and communication in UAV-assisted integrated sensing and communication (ISAC) systems.

2.9 Chapter Summary

This chapter has given a thorough overview of the challenges in wireless communication, such as spectrum scarcity, interference, and latency, alongside emerging security and energy efficiency concerns. It has highlighted the potential of UAV networks as a flexible and efficient solution to these issues, with a focus on design considerations and advanced techniques like vision-assisted beam prediction. The literature also addresses the complexities of handover management within UAV networks, highlighting the need for innovative approaches to ensure seamless connectivity. Furthermore, the integration of UAVs with computer vision technologies for blockage prediction has been discussed as a promising direction for enhancing the reliability and performance of future wireless networks. This review puts the groundwork for the following research by identifying key gaps and opportunities for innovation in UAV-assisted communication systems.

Chapter 3

Vision-Assisted Beam Prediction for Real World 5G and Beyond UAV Communication

The next era of wireless communications, specifically 5G and beyond, will be expected to deliver low-latency, ultra-reliable links for handheld devices, including UAVs, also known as drones. UAVs are increasingly recognized for their potential in offering mmWave wireless coverage in areas where traditional base stations are not feasible, such as disaster zones and rural environments. However, the highly directional nature of mmWave signals, combined with the mobility of UAVs, makes maintaining a stable connection challenging. Beamforming offers a solution to improve signal quality, but existing beam management techniques, which rely on comprehensive searches over a pre-defined codebook, introduce significant latency and incompetence, especially in high-mobility environments like UAV networks [152]. As noted by [50], UAVs have attracted considerable interest in both military and civilian fields due to their adaptability in applications such as surveillance, emergency response, and cargo delivery. When equipped with mmWave communication technologies, UAVs provide an effective solution for flexible, on-demand network coverage. This is largely due to their easy deployment and ability to LoS connections, which are vital for high-frequency communications like mmWave [153]. MmWave communications using aerial platforms have garnered significant research attention because AtG links offer LoS communications. UAVs provide benefits like flexible network reconfiguration, on-demand deployment, and a high likelihood of preserving LoS communication links. Because of this, UAVs are widely used as relays or BSs to increase network capacity and provide flexible coverage options [154]. In order to manage high-speed data transfer, UAVs may be integrated with millimeter wave communication technologies to fulfill these advanced operational demands. However, in order to maintain a sufficient SNR, narrow directional beams and large antenna arrays are required which limits the use of mmWave communications system in UAVs. The significant overhead associated with beam training due to these requirements makes it tough to support extremely mobile UAVs. Alternative solutions are required to fix these issues and improve mmWave communications for mobile UAVs [155].

However, one of the major problems in UAV-enabled mmWave technology is the overhead associated with beam training. Traditional beam management techniques usually involve extensive searches through large codebooks, which is computationally intensive and introduces significant latency, making it impractical for UAVs moving at high speeds. Furthermore, existing solutions, such as those relying solely on GPS or other positional data, often fall short in predicting the optimal beam direction in real-time, specifically in complex, dynamic environments [103].

The growing demand for high-speed, reliable UAV communication has driven research into mmWave frequency bands, despite their challenges like high path loss and low penetration. This work introduces a novel beam prediction framework that combines computer vision and ensemble learning to optimize beamforming in dynamic UAV scenarios. By integrating multi-modal data, including vision and position sensing, the study demonstrates the effectiveness of a stacked model for predicting optimal beam directions, validated using the DeepSense 6G dataset.

This chapter's remaining sections are organized as follows: An overview of the system architecture, the scenario, the dataset, beam prediction: problem formulation, and the proposed vision-assisted beam prediction approach are all covered in Section 3.1. The simulation setup and a thorough analysis of the outcomes are covered in the 3.2 section. Section 3.3, which highlights possible areas for further research, brings the chapter to its conclusion.

3.0.1 Related Work

In recent years, the issue of overhead beam training in mmWave systems has received widespread attention. Two methodologies were the focus of early efforts: (i) channel estimation utilizing compressed sensor data to exploit channel sparsity and (ii) adaptive beam codebook-based training. The technique that combines exhaustive and adaptive beam training is presented in [99] to aobtain ideal beams at the Tx and Rx. Alternatively, it is believed that mmWave channel estimation is a sparse reconstruction problem, taking advantage of the channels' inherent sparsity in [101]. A new three-dimensional beam training technology for UAV-assisted mmWave communications is proposed in [103]. It builds training beams with a flat-topped characteristic by applying the Fourier transform in inverse discrete space. Moreover, hybrid beamforming (BF) systems are investigated, which find the best beams by applying greedy geometry (GG) techniques. As beam training overhead is reduced using these conventional techniques, the reduction is only an order of magnitude, which is not sufficient in scenarios with multiple users moving around a lot.

The inability of conventional systems to adjust to highly mobile scenarios with multiple users has raised interest in solutions based on machine learning. These systems leverage past observations and additional sensing information, such as camera/vision data [100], user location [156], [157], radar data [105] and LiDAR data [104]. The integration of mmWave technologies and cameras with UAVs to improve wireless communications was covered in [155]. The authors present a system using deep learning that utilizes computer vision for predicting the direction of wireless beams, allowing UAVs to maintain a steady connection even when moving.

Similarly, using dual-mode data from visual and wireless sensing, [106] proposed a novel technique named "latency-aware visually assisted joint wireless network (VFWN)" that seeks to predict beam blockage. The global model aggregates data using a joint average technique, whereas the VFWN architecture perform data processing and model training using distributed learning at edge nodes. In addition to significantly lowering communication costs by 81.31% and delays by 6.77%, the approach obtained a 99% accuracy. Furthermore, [107] proposed an innovative solution presenting an effective algorithm to overcome the challenges in UAV-assisted networks for UAV clustering. The method incorporates group HO and cluster head (CH) selection processes, combined with network initiation and execution. However, most of the existing beam prediction systems are designed for scenarios where the UE is a person, vehicle, or robot, with movement primarily occurring in two dimensions, which simplifies the prediction process. Integrating multiple beam prediction modalities can offer a more thorough awareness of the surroundings, allowing for more accurate predictions, as noted in [158]. By combining inputs from various sensors, prediction accuracy is enhanced, and by dynamically adjusting the weight of each modality, the fusion algorithm can optimize performance and further improve prediction accuracy.

3.0.2 Motivation and Contributions

The requirement for rapid and reliable communication systems has generated interest in mmWave frequency ranges for UAV communications. But these high frequency bands have significant path loss and limited penetrating capabilities, which complicates maintaining a stable link between UAVs and ground stations. Beamforming has become a promising approach for enhancing these communication links. Nevertheless, identifying the optimal beam direction in a dynamic UAV setting remains challenging because of the highly directional and mobile characteristics of mmWave signals.

This chapter introduces an innovative approach for beam prediction utilizing multimodal data integration that minimizes the overhead of mmWave beam training. This method combines CV algorithm YOLO-v5 with ensemble learning, which use stacks approach for model training. Additionally, the study focuses on stacked neural network models to improve beam prediction in UAV communications. Stacked models are developed by integrating neural network (NN) architectures trained on different data types, such as vision and location data, and their performance is evaluated using the DeepSense 6G dataset publicly available. The primary outcomes of the chapter are given below:

- This study presents an innovative beam prediction appraoch that employs computer vision and integrative learning stacks to fuse multimodal data from vision and position sensors for training models in mmWave UAV communication, specifically customized for real-world application scenarios.

- YOLO-v5 is optimized with real-time annotations to extract relevant data, such as object classifications and the bounding box coordinates for objects detected using visual sensor information (e.g., drones or distractors).

- To achieve optimal beam prediction, a meta-learner was trained using the combined outputs of neural network modelsfor both position sensing and vision. The efficacy of the proposed appraoch was evaluated using the DeepSense 6G dataset [159].

3.1 System Architecture

This research investigates real-world wireless communication system where a mmWave base stations provide services for high-mobility UAV at a different heights. The scenario, formulation of the beam

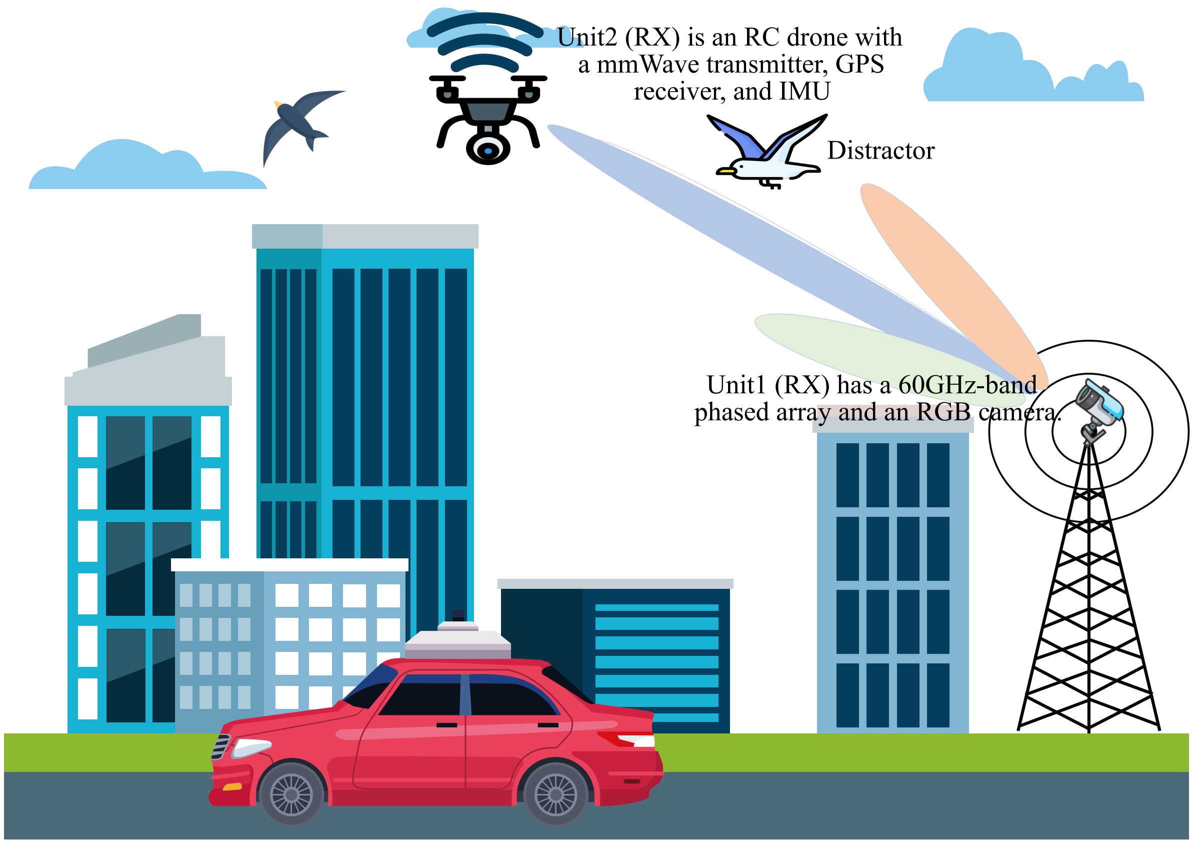

Figure 3.1: A real-world wireless communication setup, a mmWave base station connects with a UAV (radio-controlled drone) thats outfitted with GPS and an inertial measurement unit (IMU). To guarantee smooth, continuous connectivity, the base station intelligently leverages various sensory inputs, including vision data and precise GPS coordinates, enabling it to dynamically select the most effective beam for communicating with the UAV.

prediction problem, and dataset description of the framework utilized in the wireless communication system are covered in this section.

The wireless communication environment illustrated in Figure3.1 is examined in this study. In this arrangement, millimeter-wave base stations connect with extremely mobile UAV outfitted with GPS receivers capable of giving real-time location data. The base station has an RGB camera and an M-unit Uniform Linear Array (ULA), while the UAV has a single antenna transmitter. The communication system makes use of a base station with a predefined codebook $\mathcal{F} = f_n n = 1^N$, where each $fn \in \mathbb{C}^{M\times 1}$, and orthogonal frequency division multiplexing (OFDM) with K subcarriers and a cyclic prefix of length D. OFDM technology improves the efficiency of UAV data transmission by splitting signals into multiple subcarriers, while the cyclic prefix mitigates inter-symbol interference caused by multipath propagation. In a downlink situation, the received signal at the UAV can be described as follows: if the wireless channel between the drone and the base station at time t is represented by $h_k[t] \in \mathbb{C}^{M\times 1}$, then for the k_{th} subcarrier, the UAV receiving signal can be written as follows:

$$y_k[t] = h_k^T[t] f_n[t] x + z_k[t], \tag{3.1}$$

where the noise level is denoted by $z_k[t]$ and the beamforming vector is represented by $f \in \mathcal{F}$. Here,

$f^*[t] \in \mathbf{z}$ represents the optimal beamforming vector at time t, optimized to maximize the average SNR. The variable $\mathbf{z}$ denotes the set of all predefined codebook beamforming vectors [152]:

$$f^*[t] = \arg \max_{f_n[t] \in \mathcal{F}} \frac{1}{K} \sum_{k=1}^{K} \mathrm{SNR} |h_k^T[t] f_n[t]|^2. \tag{3.2}$$

High-frequency electromagnetic waves are used in mmWave technology to facilitate fast communications over a short distance. Beamforming techniques are used by mmWave base stations to direct signals to UAVs, resulting in reliable and steady communication connectivity. The UAV's position, movement trajectory, and different environmental conditions are only a few of the characteristics that the base station considers optimizing the beamforming process.

3.1.1 Beam Prediction: Problem Formulation

In order to determine which beam $f^*[t]$ is optimal from the predetermined codebook $\mathcal{F}$, the transmitted symbol x in equation 3.1 needs to comply with the constraint $\mathbb{E}[|x|^2] = P$. The average power of each symbol is denoted by P, and equation 3.2 maximizes P. In traditional mmWave systems, obtaining the ideal beam involves extensively scanning a specific codebook or using explicit channel state data. Although a thorough search will result in a significant training overhead, obtaining channel information in high-frequency communication situations is extremely challenging. As a result, this study uses CV and ensemble learning (particularly stacking) to combine multimodal visual and position sensor information collected by uavs or base stations. With the multimodal data set, the corresponding RGB set is represented as $X[t] \in \mathbb{R}^{HXWX3}$, where H, W, and 3 represent height, width, and color channel number, respectively. The transmitter's height, distance, in a 2-D position vector at time t are all included in the position data $g[t]$. Determining the mapping function f_Θ for the ideal beam index prediction $f\hat{[t]}$ from the codebook $\mathcal{F}$ is the aim of this problem. It may be represented mathematically as:

$$f_\Theta : \mathscr{D}[\sqcup] \longrightarrow f\hat{[t]}, \tag{3.3}$$

where $\mathscr{D}[\sqcup]$ indicates the aggregated dataset that includes position and visual sensing.

3.1.2 Proposed Vision-Assisted Beam Prediction Model with Stacked Architecture

An ensemble stacked classifier intended to take advantage of two distinct data modalities is presented in this section: RGB images and GPS information. The objective is to create a model that can accurately execute the mapping described in equation 3.3. The procedure is to stack the YOLO-v5 outputs with the outputs of a subsequent NN. More specifically, YOLO-v5 outputs (bounding boxes and class probabilities for items spotted in an image) are fed into another NN. Based on these inputs, the subsequent NN processes the data further and generates predictions.

The motivation behind stacking YOLO with NN is to enhance the overall performance of the system. By adjusting the bounding box dimensions, the secondary neural network can improve its object identification capabilities or produce accurate final predictions using the detailed information provided

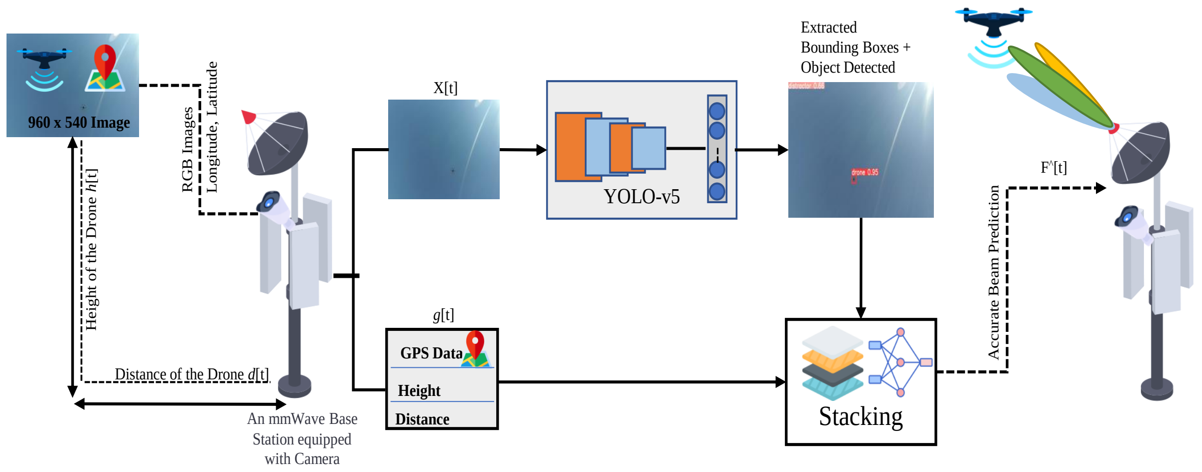

Figure 3.2: An overview of the stacking model architecture developed to optimize wireless communication between the UAV and its environment. To detect objects and generate bounding boxes around the UAV, the architecture uses YOLO-v5 to process UAV images. Based on these bounding boxes, along with wireless and positional data, a stacking model is subsequently employed to determine the optimal beam for efficient wireless communication.

by YOLO-v5. This synergistic approach aims to harness the strengths of both components to achieve optimal prediction accuracy and system efficiency. To summarize, stacking YOLO-v5 with a NN is an effective appraoch for developing advanced systems capable of object detection and other operations. This approach takes advantage of the combined capabilities of YOLO-v5 and neural networks to outperform the accuracy and performance possible with either technology alone. The combination of YOLO-v5's precise object detection and neural networks' adaptive processing power enables the development of extremely efficient and accurate prediction models. Figure 3.2 depicts the architecture and operational dynamics of this proposed stacking approach, demonstrating how different technologies interact to improve system capabilities.

Algorithm 1: Optimal Beamforming Prediction

Data: Training data $\{({x_{img}}^{(i)}, {x_{pos}}^{(i)}, y^{(i)})\}_{i=1}^{N}$, where ${x_{img}}^{(i)}$ and ${x_{pos}}^{(i)}$ are the image and position vector inputs respectively for the i-th sample, and $y^{(i)}$ is the corresponding true label vector.

Result: Meta learner $f(\cdot)$

begin

Train a model based on images to produce predictions. ${y_{img}}^{(i)}$ for each input ${x_{img}}^{(i)}$;

To make predictions, train a position-based model ${y_{pos}}^{(i)}$ for each input ${x_{pos}}^{(i)}$;

for $i = 1$ *to* N **do**

Combine the predictions to form the input vector $x^{(i)} = [{y_{img}}^{(i)}, {y_{pos}}^{(i)}]$;

Obtain the prediction vector $\hat{y}^{(i)}$ using the meta learner $f(\cdot)$;

Train the meta learner by minimizing the cross-entropy loss;

$\mathscr{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{64} y_j^{(i)} \log(\hat{y}_j^{(i)})$;

3.2 Simulation and Results Analysis

To evaluate the proposed beam prediction methodology within a millimeter-wave (mmWave) drone communication framework, the DeepSense 6G dataset [159] is employed. The simulation system utilized in this study is fully summarized in the following section.

3.2.1 Description of the Dataset

The freely available DeepSense 6G dataset contains a wide variety of multimodal data sources, such as GPS data, LiDAR, radar, and vision sensing (images). Acquired from an actual wireless communication testbed, this dataset is particularly applicable for investigating the practicality and efficacy of the proposed beam prediction solution. This section aims to briefly review the scenario covered by the DeepSense 6G dataset and delve into the composition of the final dataset employed for the development and validation of the sensing-assisted beam prediction methodology. For exploring high-frequency wireless communications with UAVs, Scenario 23 from the DeepSense 6G dataset has been selected. This scenario features a stationary base station (Unit1 - RX) equipped with a 60GHz band phased array and an RGB camera of standard resolution. The phased array, designed to capture signals, is configured with an oversampled set of 64 predefined beams (Q=64) and 16 elements (M=16), enhancing its capability to receive a wide range of signals accurately.

To broaden the FoV of the base station, both the RGGB cameras and the mmWave phase array are positioned on a surface with purpose, about 1.5 meters above the ground, oriented upwards. This setup ensures comprehensive coverage and signal reception from various angles. Unit2 (RX), an RC drone, is equipped with GPS, a mmWave transmitter, and IMU. The UAV Tx, featuring a quasi-omnidirectional antenna, consistently operates at the 60 GHz frequency, ensuring continuous communication with the base station. The scenario is specifically designed to augment the dataset's diversity, allowing the UAV to operate at varying heights, distances, and speeds relative to the base station. This variability introduces a wide range of conditions and challenges typical of real-world UAV operations in high-frequency wireless communication settings, making it an invaluable resource for testing and validating the proposed beam prediction solution.

3.2.2 Configuration for Simulation

The simulation of the sensing-aided beam prediction model leverages the diverse data collected across different sensing modalities, including position, height, distance, and visual information. For analytical purposes, data related to position, height, and distance are amalgamated into a single modality, while visual data is treated as an independent modality. The data set, which comprises multimodal data, was split 70/30 for training and validation. The training set was used to develop the prediction model, while the validation set assessed its generalization capability. The YOLO-v5 and stacked model was trained in the Google Colab environment, which uses free-tier hardware resources. The system included a NVIDIA Tesla T4 GPU with 15 GB of VRAM, two virtual CPU cores, and 12-15 GB of shared RAM. This setup provided sufficient processing capacity to efficiently handle the training processes, ensuring that deep learning experiments could be carried out within the limits of a cloud platform.

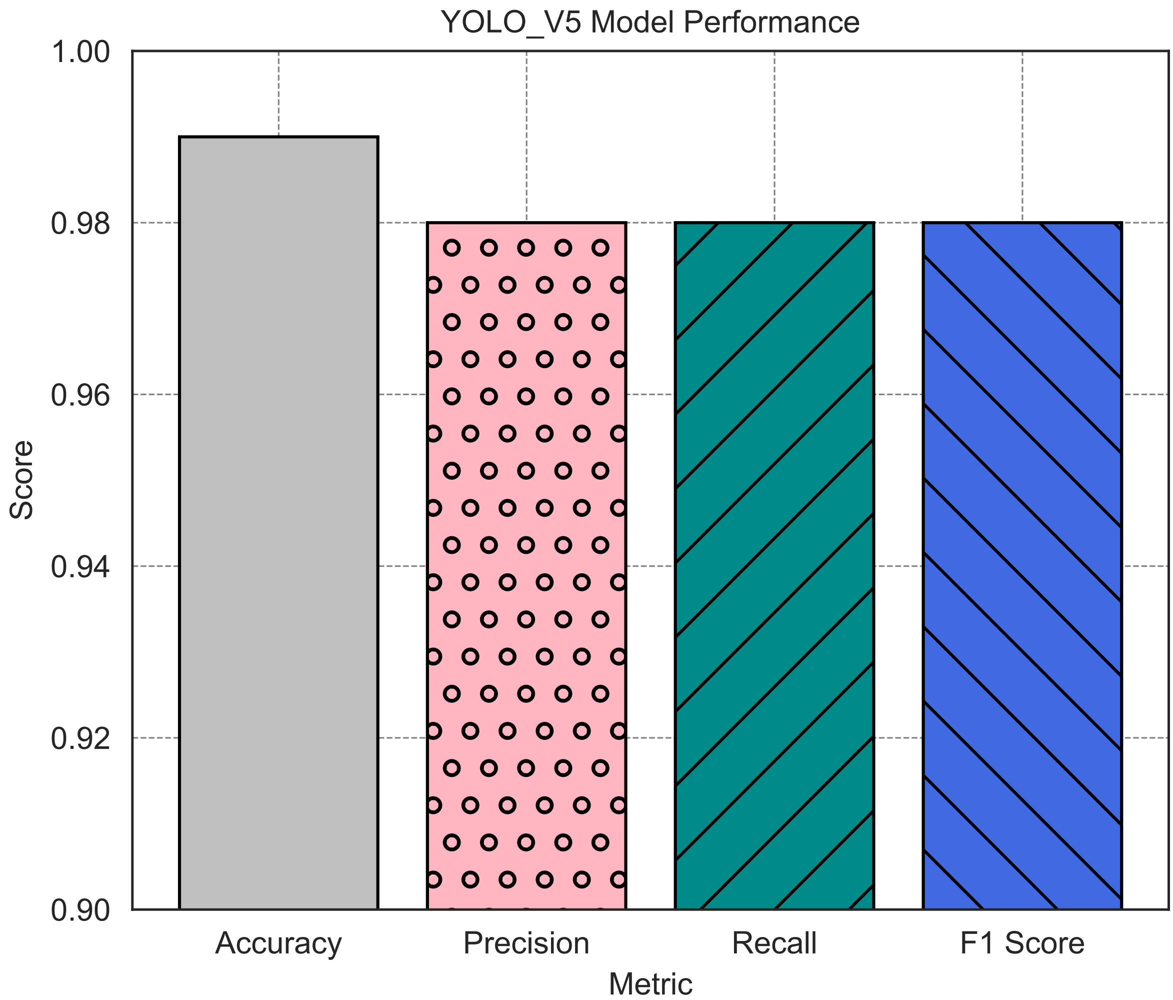

Figure 3.3: The YOLO-v5 model, trained to predict the UAV location, is shown in this figure along with its recall and precision curves. Based on object detection and bounding box data, the model can consistently predict the UAV position.

YOLO-v5 Training: The YOLO-v5 framework is employed to recognize the UAV and pinpoint its location (via bounding boxes) within the input imagery, which also features distractor elements. These input images are standardized to dimensions of 960 x 540 pixels. For the training phase, YOLO-v5 is configured with a batch size of 8 and undergoes 100 epochs of training. The dataset earmarked for this process comprises 600 images for the training segment and 29 images dedicated to validation purposes. Post-training, the YOLO-v5 model is tasked with identifying the UAV and its bounding boxes across the entirety of the DeepSense image dataset, ensuring a comprehensive application of the trained model for drone detection and localization.

With an overall precision of 0.98% and a recall of 0.98%, the YOLO-v5 model can identify UAVs from aerial images. Figure refyo displays the recall and precision of the YOLO-v5. These results show that the YOLO-v5 model can localize and identify UAVs with high reliability even in difficult outdoor environments, which makes it a useful tool for a range of applications such as search and rescue operations and surveillance.

Training Neural Network: Bounding box coordinates, altitude, GPS (latitude, longitude), and the distance from the wireless sensor are the inputs used to train the neural network. The neural network uses a modified linear unit activation function and is composed of two dense layers, each with 512 neurons. The output layer employs sparse categorical cross-entropy as the loss function and softmax activation with 64 categories. The neural network was trained with a batch size of 32 and 90% train to 10% test over 100 epochs. LR decays by a factor of 0.1 at epochs 20, 40, and 80, with the learning rate set at 0.01. We adjust the network's hyperparameters in accordance with the values listed in the table 3.1. Using the same set of training and validation data as the prior modality-specific model, we employ a stacked model for the vision-assisted approach, which combines YOLO-v5 with a neural network model to predict the optimal beam index.

We utilize a remained data that was not utilized for training or validation in order to assess the proposed model. We evaluate the proposed model's efficacy by comparing it with the state of the art methods. We use standard metrics like accuracy, recall, precision, and F1 score for this analysis. The overall goal of the simulation scenarios is to assess how well the suggested model works to improve the accuracy of beam predictions for different sensing modes.

Table 3.1: Hyper-parameters in Training and Design

Parameters	**YOLO-v5 Training**	**Neural Network**
Input	960 x 540 Images	Bounding box
Batch size	8	32
Epochs	100	100
Learning rate	0.01	0.01

3.2.3 Results Discussion

The evaluation of the proposed model's performance reveals noteworthy results in relation to accuracy overall, recall, F1 score, and precision. Specifically: The model exhibits a precision rate of 0.8888, signifying that its positive predictions are accurate 88.88% of the time. This high precision underscores the model's effectiveness in correctly identifying true positive instances among all positive predictions. With a recall rate of 0.8855, the model demonstrates its capability to correctly identify 88.55% of all actual positive cases. This measure is critical for instances where ignoring a positive occurrence may have major effects, indicating the model's robustness in detecting relevant signals. The model's F1 score stands at 0.8853, as detailed in Table 3.2. The F1 score, which is the harmonic mean of recall and precision, provides a fair assessment of the model's performance, particularly when it is important to have recall and precision in balance. The overall accuracy of the model is reported at 0.8910, meaning it correctly classifies 89.10% of all instances. This metric highlights the model's general effectiveness across a variety of conditions and instances.

These results, visualized in Figure 4.8, collectively demonstrate that the proposed beam prediction model is both reliable and efficient. Its high precision and recall rates suggest that it can serve effectively in various practical applications, such as monitoring, surveillance, and search-and-rescue operations, by reliably locating and identifying drones in challenging outdoor environments. The F1 score and accuracy further reinforce the model's robustness and its potential as a valuable tool in the context of mmWave drone communication systems.

Table 3.2: Comparison of the Different Evaluation Metrics

Model	Precision	Recall	F1-Score	Top-1 Accuracy
Vision	0.8567	0.8549	0.8587	0.8632
Position	0.5803	0.5603	0.5788	0.6034
Proposed	0.8888	0.8855	0.8853	0.8910

The proposed model has accuracy and recall scores of 0.8888 and 0.8855, respectively, indicating that it performs extremely well in predicting instances of the target variable. The model's excellent predictive abilities are further highlighted by its F1 score of 0.8853 and accuracy score of 0.8910. Compared to baseline vision-only and position-only models, the proposed stacked model improves accuracy by 4.5% and recall by 3%, demonstrating its advantage in integrating multimodal data, with recall scores as 0.5603 and 0.8549, as well as accuracy values of 0.6034 and 0.8632.

These results underscore the proposed model's enhanced predictive power and its ability to accurately classify instances of the target variable with a high degree of reliability. Particularly, the model achieves higher precision, recall, F1 score, and accuracy compared to both vision-based and position-based models. This dominance implies that the suggested framework is more effective in detecting instances of the target variable, making it a more dependable option for accurate predictions in a wide range of applications.

In conclusion, the assessment metrics given for the proposed model demonstrate its high effectiveness in predicting target variable occurrences, significantly outperforming vision-based and position-based models. This shows the model's potential as a highly reliable approach to accurate beam prediction in mmWave drone communication systems, with important implications for monitoring, surveillance, and search-and-rescue missions.

The proposed model achieves significantly better results than both vision and wireless-based approaches on all four assessments. In particular, the model outperforms the other two appraoches in terms of accuracy, F1 score, precision, and recall. These findings suggest that the proposed framework is more proficient at accurately identifying instances of the desired variable, making its accurate predictions more reliable. To sum up, the proposed model outperforms vision and wireless-based approaches in terms of prediction of the target variable, according to the evaluation metrics.

Figure3.5 presents a graph that utilizes four distinct techniques; actual beam power, position, vision, and the proposed stacking technique shows significant enhancements in beam gains when applying the stacking approach over other single-modality strategies such as vision and position alone. This analysis underscores the efficacy of the proposed stacking method, although it also points out minor discrepancies between the estimated beam gains and those initially designed for various UAV positions.

Figure 3.5 depicts a graph that shows the power levels of both the predicted and actual beams. It demonstrates that predictions with improved top-1 accuracy closely match the actual beam power. However, lower top-1 accuracy results in large differences between the predicted and actual power, which can lead to undesirable performance decreases

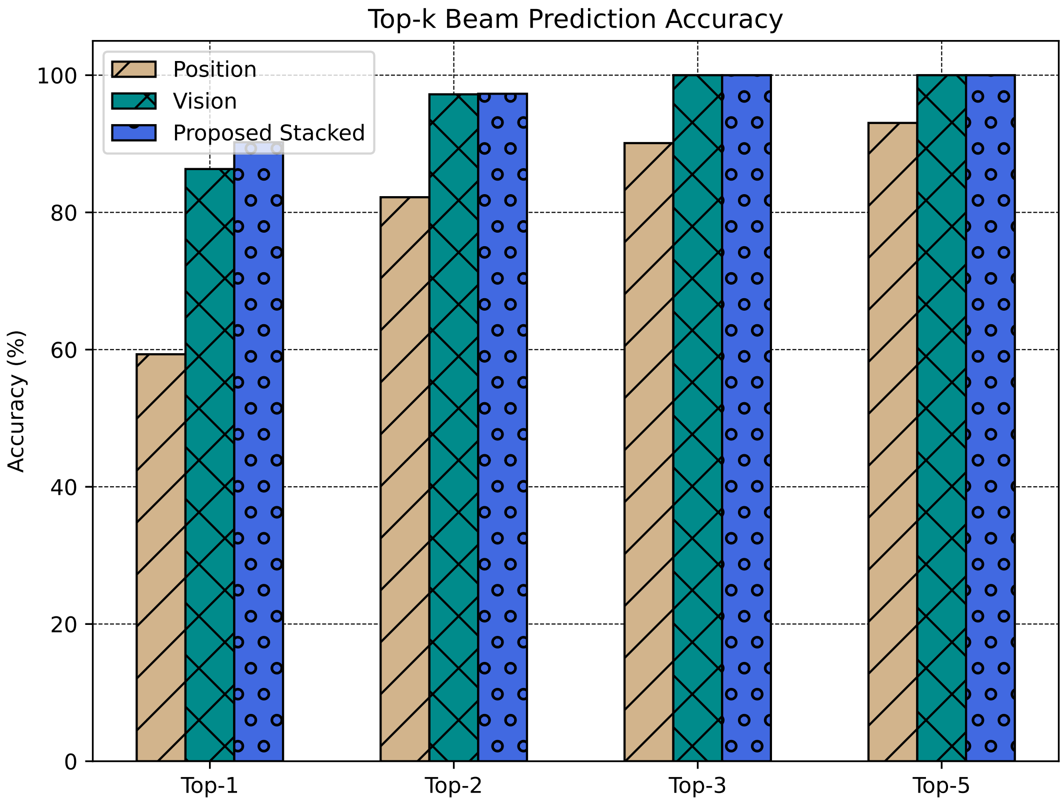

Figure 3.4: Top K-beam predictions using the stacked method. The graph depicts the accuracy scores of the position, vision and proposed stacking model.

These insights are particularly compelling, emphasizing the advantage of integrating position and vision-based methods to refine beam prediction in UAV operating within mmWave communication frameworks. By adopting such sophisticated techniques, it's possible to enhance the precision and dependability of the communication process, thereby facilitating more effective data transmission and reception. This advancement holds significant promise for applications requiring high-speed, low-latency connectivity, such remote healthcare systems and driverless cars, and automated manufacturing processes.

The variations observed in low-accuracy predictions can be attributed to a variety of technical issues that influence the alignment of the predicted and real power levels. One key problem is UAV height changes, which can change the propagation environment and effect signal attenuation, resulting in power estimation errors. Furthermore, interference from adjacent UAVs or other wireless devices can produce unexpected variations in received power, which contributes to predicting mismatches. Environmental variables such as obstacles in the line-of-sight path, weather impacts (e.g. rain or fog), and multipath reflections all contribute significantly to signal power distortion. These factors add complications to the model's forecast accuracy, especially in dynamic or uncertain environments.

Leveraging the combined strengths of mmWave technology and drones through these innovative methods opens a plethora of new possibilities, setting the stage for groundbreaking developments in the future. This approach not only optimizes the utilization of mmWave technology but also paves the way for exploring new horizons in various high-tech applications, ensuring that the potential of such advanced communication systems is fully realized.

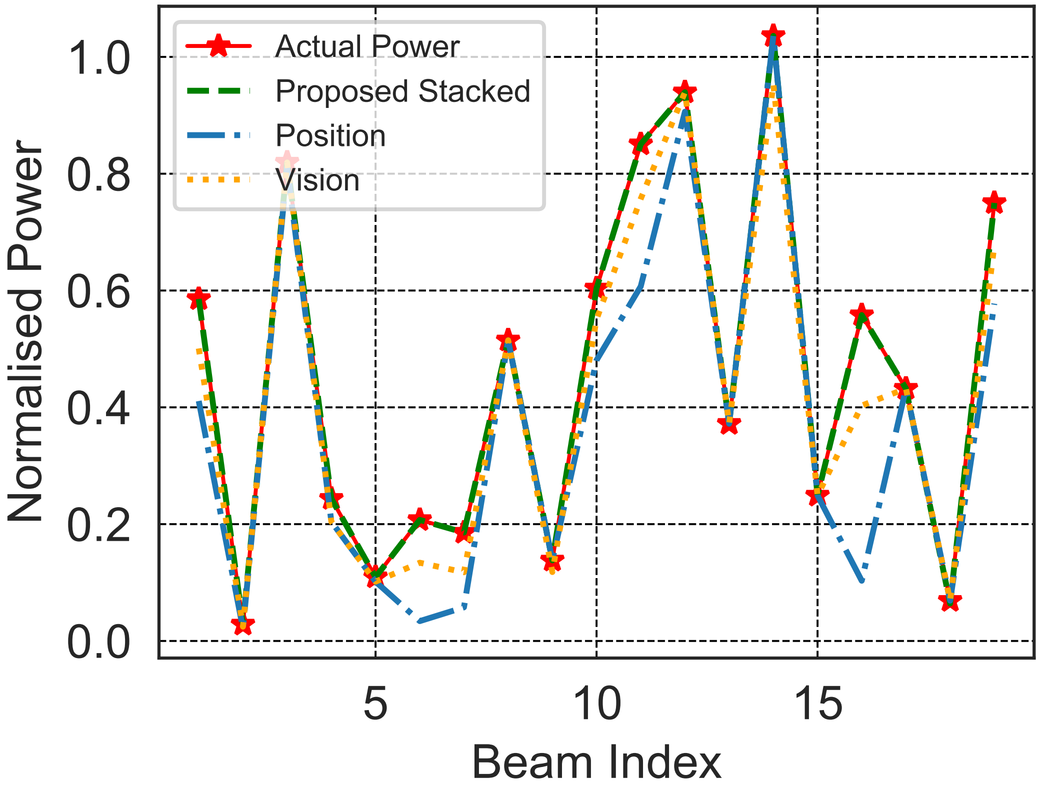

Figure 3.5: Top-1 normalized power between the position model, the vision model, and the proposed approach in comparison to the codebook's actual power values.

3.3 Chapter Summary

This chapter explored the enhancement of UAV communication in 5G and beyond networks using millimeter-wave (mmWave) technology. The study addressed the challenge of high overhead in beam training for highly mobile UAVs by introducing a novel beam prediction framework that combines computer vision and multi-modal data fusion through ensemble learning.

The proposed method significantly outperformed traditional models, achieving a top-1 accuracy of approximately 90% and near 100% for top-3 and top-5 predictions. This improvement is crucial for applications requiring high-speed, low-latency communication, such as autonomous vehicles and smart manufacturing.

This chapter proposes an innovative solution for dynamic beam prediction, achieving near-perfect accuracy in top-3 predictions. Future work could explore real-time deployment in highly dynamic environments, enhancing autonomous vehicle and smart factory operations.

Chapter 4

UAV-Assisted Handover with Proactive Blockage Prediction for Future Wireless Communication

The previous chapter introduced an innovative Mmwave beam prediction technique that uses stacking to combine ensemble learning with CV. The technique integrates multi-modal visual sensing and location data to accurately estimate UAV positions and orientations. Building on these beam management techniques, this chapter presents a proactive blockage prediction mechanism using UAVs as base stations for HO. Proactive HO is essential to maintain LoS and ensure reliable mmWave communication. The technique requires continuous knowledge of the surrounding wireless network and employs CV for detecting possible blocking objects, user speed, and location.

Using publicly available datasets for blockage prediction, the proposed scheme evaluates the efficacy of proactive HO. By combining vision wireless (ViWi) and uav channel modeling scenarios, this work produces significant wireless data samples. Furthermore, polarization matching scenarios are incorporated into UAV antenna modeling to optimize signal reception.

The findings demonstrate that in addition to ensuring uninterrupted connectivity, UAV-assisted handover improves overall network performance by 20%. This blockage prediction mechanisms have greatly contributed to the development of proactive blockage mitigating solutions in wireless networks. This study demonstrates that UAVs have the potential to increase Mmwave communication reliability and efficiency by serving as dynamically flexible base stations.

These findings highlight the practical benefits of leveraging UAVs for proactive handover, demonstrating a clear pathway toward more resilient and efficient communication networks. By integrating advanced CV techniques and proactive strategies, this approach significantly enhances the capabilities of mmWave communication systems, ensuring uninterrupted connectivity and improved performance.

4.1 Introduction

It is believed that THz and mWave communication technologies would be critical in meeting the increasing demand for greater data transfer capabilities [160]. These advanced technologies facilitate extensive connectivity, more bandwidth and ultra-reliable low-latency communications (URLLC) are required for complex operations like intelligent healthcare systems, the Industrial 4.0 revolution, holographic telepresence, augmented and virtual reality (AR/VR), and autonomous vehicles[161, 162]. Furthermore, the concept of ultra-dense networks (UDNs) is established by the adoption of higher frequency bands, which encourage the development of small coverage cells [163]. Next-generation networks will use multi-array antennas with MmWave and THz frequencies, allowing for beamforming that directs radio signal power precisely toward the receiving device through LoS communication [164]. Despite their various advantages, mmWave and THz technologies generally experiencing significant penetration losses; adapt to mobility problems and increased sensitivity to obstacles. For example, when the communication channel is blocked by obstacles such as vehicles or people, the link budget may result in a power attenuation of 20 dB or more [165]. Thus, these sophisticated approaches mainly depend on the LoS communications between the BS and the designated users [160, 166].

It is possible to properly handle the problem of link congestion through a better understanding of the wireless network environment, enabling prediction of potential congestion. The conventional methodology for tackling this issue involves the integration of machine learning techniques with wireless sensor data (for instance, channel information and received signal strength metrics). Recent research demonstrates both proactive and reactive blockage prediction methods leveraging data from sensors [167]. Although reactive blockage predictions do not meet the strict low-latency requirements, proactive blockage prediction is still in its early stages and requires further investigation. This chapter explores future developments in blockage prediction capabilities, emphasizing the integration of UAVs as dynamic base stations to improve decision-making and maintain seamless connectivity in high-mobility scenarios.

UAVs are acknowledged as crucial facilitators for various services, including smart city projects, health care, real-time surveillance, disaster reply, and wireless communication infrastructure [152]. Because of their installation and airborne positioning capabilities, UAVs are conceptualized as airborne BSs that are amenable to facilitating massive MIMO,3D MIMO and mmWave communication network [168, 169, 170]. UAVs are frequently used as aerial BSs or relays to expand network capacity and offer flexible coverage options [154]. Motivated by the potential for UAV-aided communication, this chapter highlights proactive blockage prediction in UAV-assisted HO using visual and wireless data. Users who have performance concerns switch to alternative base stations during the HO process that offer higher signal strength. Nevertheless, the efficacy of handover processes is contingent upon the availability of environmental data and proactive blockage predictions. Moreover, erroneous or excessive handover occurrences result in increased latency, diminished throughput, and a reduction in the overall QoS. As a result, blockage prediction has emerged as a dynamic field of inquiry aimed at identifying new and flexible strategies to maintain the reliability as well as the efficiency of wireless networks.

4.1.1 Related Works

Despite the myriad advantages associated with Mmwave and THz communication, utilization of these elevated frequency bands raises a plethora of challenges, particularly increased training overhead and increased sensitivity to LoS obstacles [171, 172]. Consequently, such obstacles lead to a notable decline in QoS. One viable strategy to mitigate this issue is the implementation of multi-connectivity, which enables users to establish simultaneous links with multiple BS [173]. In this framework, A central con-

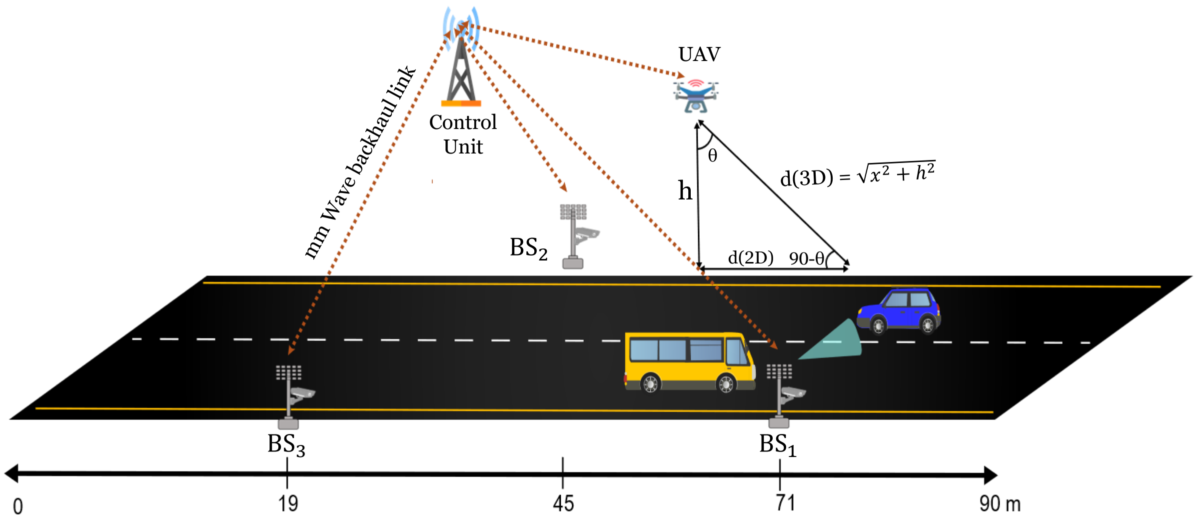

Figure 4.1: A UAV-based vision-assisted wireless communication infrastructure with three RGB-camera-equipped base stations, a UAV base station that covers areas where signals are blocked, and central control.

trol unit receives a measurement report from each base station, which assesses the connectivity quality for the user it is connected to. This central unit then coordinates an optimal scheduling system that maintains the communication link's quality. Yet, it is noteworthy that multi-connectivity algorithms predominantly exhibit a reactive nature, being activated in response to obstructions. Moreover, these algorithms exacerbate the scheduling overhead and induce undesirable latency [160].

An alternative approach to ensure uninterrupted connectivity in high-frequency communication is the employment of HO. Nevertheless, the efficacy of the HO mechanism is contingent upon the acquisition of prior knowledge regarding the environment and real-time information concerning link obstructions. Consequently, an array of investigations has been undertaken to address the challenge of predicting link obstructions. Predictive methodologies, particularly those focused on beam prediction tasks, have garnered increasing attention in the context of ML applications in recent years. These methodologies predominantly aim to harness supplementary information to enhance comprehension of the wireless environment [152]. For instance, various studies have supported the use of ML techniques to forecast link obstructions by utilizing wireless sensor data, such as received signal strength (RSS) and channel characteristics [173, 174]. .However, these investigations typically engage in reactive measures that adversely affect the execution of the communication notwork.The authors of [175] propose a proactive blocking prediction technique designed for Mmwave communications, drawing inspiration from the capabilities of ML models. The suggested method trains gated recurrent units (GRUs) to predict link congestion using beamforming sequences. Although this technique is characterized by its simplicity and efficacy, it is especially vulnerable to unexpected changes in channels, mainly because of its reliance on one data modality. The article in [176] suggested the employment of sub-6GHz channels to anticipate forthcoming link obstructions, thereby enabling foresight regarding future dynamic or mobile blockages. Furthermore, within the domain of mmWave and THz networks, the anticipation of signal blockages continues to represent a formidable challenge due to the inherently dynamic nature of environmental transformations. A recent investigation [177] introduces a framework intended to address this challenge by amalgamating computer vision with distributed on-device learning. This framework capitalizes on semantic information extracted from images to enhance the precision of obstruction predictions.

The utilization of multi-modal data in conjunction with the integration of DL and CV are innovative methods that seek to solve the high-frequency communications systems link congestion problem. Merging of multimodal data enables wireless communications to enhance awareness of surrounding environments, which is anticipated to assume a critical function in the future landscape of wireless communication, particularly concerning blockage, HO, and network resource distribution. Several preliminary studies exploiting the combined potential of multimodal CV and DL have been reported in the academic articles. For example, [178] introduced a vision-aided proactive HO approach that uses depth images in combination with wireless data. Using multi-modal data, a deep learning model is carefully trained to reveal a relationship between measured throughput and depth images. This method is useful for estimating future link quality offering timely insights for effective handover decisions. In the same way, [171] train deep learning models to predict congestion ahead of time using RGB images and beam forming vectors. The growing adoption of ML based solutions is increasingly evident, resulted from the limitations of conventional methods for handling extremely dynamic, multi-user settings. These advanced systems are thoughtfully designed to leverage past research findings and utilize a range of sensing modalities, such as user positioning [102], camera-based visual imagery [100], LiDAR scans [104], and radar information [105].

It is evident from the research findings published in the literature that using multimodal data can greatly increase the performance of wireless network. Nonetheless, most methods that leverage multimodal data are capable of predicting potential blocking but not sufficient to perform the necessary actions to ensure uninterrupted connectivity.

4.1.2 Motivation and Contributions

As previously discussed, the implementation of mmWave presents numerous complex challenges. However, the obstruction of communication links represents a critical impediment for high-frequency transmission. The prospective evolution of wireless communication necessitates enhanced QoS accompanied by uninterrupted connectivity to accommodate real-time applications. Consequently, proactive HO emerges as a promising strategy to uphold connectivity by transitioning the user over to an alternative LoS connection. Nevertheless, proactive HO effectiveness depends on the having the prior knowledge regarding link obstructions to facilitate timely interventions. The integration of multi-modal techniques, it is expected that, when combined with CV and DL, wireless networks will operate more smoothly in this environment.

A previous research study presented a novel CV-aided HO technique that uses multi-modal data, integrating wireless data (RSSI) with vision (RGB pictures) [164]. This approach introduced a new type of handover event, called a blockage event (BLK), which identifies potential blockages when the user falls within the vision sensors field-of-view (FoV). By combining CV with multi-variate regression, a handover metric, called time to block (T_{blk}), is determined, allowing proactive actions to ensure continuous connectivity. However, path loss during user mobility between base stations may lead to a reduction in signal strength.

To tackle this problem, this chapter present a UAV-assisted handover approach that employs a synthesis of RGB images and wireless data as indicated by the RSSI. To find users, possible obstacles, user localization, and clearance from obstacles, the suggested approach makes use of object detection and localization (ODL) algorithms. Moreover, a neural network has been used to predict the handover time, T_{blk}, and appropriate corrective actions are carried out if conditions permit sufficient time for the handover process.

To improve coverage in obstructed areas, a UAV deployed at a specific altitude serves as a BS. When an obstruction is identified (triggering the *BLK* event), the proposed algorithm the proposed method sends a handover request to ensure that the user's transition to the UAV occurs smoothly. This process guarantees uninterrupted connectivity while enhancing the signal quality. This chapter's key contributions are outlined as follows:

- The chapter presents UAV-assisted handover using CV and ML to address the problems resulting from connection blockages in high-frequency communications. Multimodal data is used for proactive blockage prediction, which helps to ensure a successful handover with little performance degradation. The combination of CV and multimodal data increases the network's awareness of its environment significantly, which raises the accuracy of blockage prediction.

- We have formulated an analytical framework for dipole antennas that can be used for UAV-ground communication, as well as a channel model for UAV base stations. Furthermore, a detailed evaluation is undertaken to examine how path loss affects RSSI, taking into account the UAV's position at different altitudes.

- Lastly, comparative evaluation of UAV-assisted versus traditional non-UAV handover processes illustrate the efficiency of the proposed approach. According to the empirical results, UAV-assisted HO mechanism accounts for an approximate 20% boost in RSSI.

4.2 System Model

This research leverage visual data and wireless signals in conjunction with DL methodologies to anticipate potential blockages and facilitate pro-active handover procedures. The premise is to integrate diverse technologies such as CV, DL, and UAV-supported communication to enhance wireless transmission within elevated frequency spectrum. The subsequent subsections offer a comprehensive exposition of UAU-assisted vision-enhanced wireless communication.

4.2.1 Scenario Description

This study considers a high frequency wireless network framework designed to encompass a city street with a length of 90 meters and a width of 15 meters, as shown in Figure 4.1. The architecture includes 3 SBS, a central unit, and UAV-BS positioned at a designated altitude "h," which collectively address the obstruction zone. A uniform linear array (ULA) antenna with M elements is installed on each SBS. Beamforming is used for establishing a LOS link that enhances the signal. In the unlicensed 60 GHz frequency spectrum, the communication system exploits OFDM. For 60 GHz multi-antenna OFDM systems, a codebook-based beamforming technique is described in [179]. Additionally, standard

RGB cameras are installed in every SBS to monitor the surroundings and gather visual information for predicting possible obstacles. To facilitate efficient HO, UAV serves as a substitute to the SBS and extends network coverage to blockage regions. To facilitate efficient HO, the UAV serves as a substitute to the SBS and extends network coverages to blockage regions. To simplify the scenario, As illustrated in Figure. 4.1, we take into account, one stationary obstruction (a bus), one mobile user (a car), three SBSs that cover the whole length of the road, and a fixed UAV above the blocked region. Sensors at the SBSs gather wireless and visual environmental data, which is subsequently sent to the control unit (CU) via a point-to-point 10 Gbps mmWave backhaul connection [180]. The CU functions as the system's central processing unit, collecting and analyzing relevant information to develop the ML model for proactive obstruction prediction. Additionally, the CU leverages real-time data to ensure a seamless handover process after the model was successfully trained.

4.2.2 UAV Channel Modelling

To understand air-to-ground channel characteristics of communication involving UAVs, this study investigates LOS communication. When a mobile vehicle enters the designated area, visual sensors track the user and detect possible obstructions. The UAV is strategically positioned in response to the presence of an obstructing entity, as illustrated in Figure 4.1. An omnidirectional antenna is recommended for AtG communications in UAV operations to reduce alignment issues between the transmitter and receiver (Tx/Rx) that can arise because of the rapid speed of driving cars. In comparison, directional antennas may be appropriate when both the Tx and Rx are static or experience minimal movement, provided the antenna patterns can be adjusted in real time.

In situations where UAV operation is clear, the crucial role of the LOS component in the elevation plane for determining the power received by the co-polarized antenna is determined by the antenna gain. We have developed an analytical path loss model that considers antenna gain in the elevation plane to address this issue. Our study includes an in-depth analysis of various UAV altitudes, antenna orientations, and the influence of angle of elevation on received power.

A significant factor in network communication is antenna polarization. Establishing a communication link becomes impossible even in LOS conditions, for example, if the transmitting (TX) antenna on a UAV is vertically polarized (V) while the receiving antenna is horizontally polarized (H), or vice versa. Improper alignment of antenna orientations can result in significant losses due to polarization mismatch in received signal strength, even when the UAV is close to the ground receiver [181]. As a result, precise antenna polarization alignment is important. Figure 4.2 shows the reduction in received power caused by polarization mismatch. In cases where antennas are aligned with vertical-horizontal (V-H) polarization, complete signal loss occurs. V-V or H-H alignments provide the strongest signal possible; a signal loss of 0 dB indicates the highest received power. When receiving a linearly polarized signal with a circularly polarized antenna, a loss of 3 dB (or the equivalent in reverse) may be experienced, but this is generally manageable. Using orthogonal antenna polarization leads to the highest power loss, as attenuation exceeds theoretical limits. However, since most antennas have minimal polarization decoupling, practically speaking, the loss will never reach infinity.

This work present a comprehensive analytical framework addressing the scenario of a dipole (or monopole) antenna utilized for the connection between a ground terminal and a UAV. Both antenna

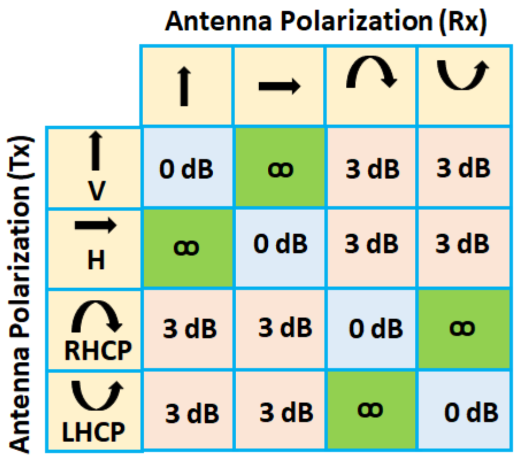

Figure 4.2: A conceptual diagram illustrating the different scenarios of polarization misalignment and the resulting mismatch losses. The direction of the highest vector of the electric field is referred to as polarization. If the direction of an incoming electromagnetic signal doesn't match the receiving antenna's orientation, it can make communication links completely inoperable.

types display similar radiation characteristics; consequently, the identical mathematical model is applicable in both instances.As a result, subsequent analyses will concentrate on the dipole antenna. In three-dimensional space, a dipole antenna produces a radiation pattern resembling a doughnut shape, while in a two-dimensional E-plane view, the pattern appears as an 8-shaped pattern. Understanding the antenna's radiation patterns is paramount, as the LOS scenario is naturally paired with the antenna's connectivity within a specified direction. The three-dimensional radiation patterns are also represented in two dimensions, as illustrated in Fig. 4.3. Depending on the orientation, it is possible to obtain the dipole, an elevation cross-section (y-z or x-z planes, referred as E-plane), or a horizontal cross-section (x-y plane). In [181], a sinusoidal function was used to model the elevation gain of the antenna, as the UAV was maintained in a hovering position while the receiver (RX) remained stationary. In this particular context, the bore-sight direction of the antenna, $\theta = 0°$, results in null radiation, as $\sin(\theta)$ or $\cos(90° - \theta)$ equals zero, whereas the maximum radiation is achieved at angles of 90°and 270°. In contrast, the present study examines a dynamic user scenario, specifically a car, as the UAV is imagined as stationary. This scenario requires optimal gain along the LOS, meaning that the antenna's radiation pattern should demonstrate maximum directivity at 0 and 180 degree angles, respectively. The horizontal placement of the dipole antenna results in ideal configuration, as illustrated in Figure. 4.3 (b). The horizontal (x-y) plane in this configuration forms a directed plane, offering a two-dimensional, 8-shaped radiation pattern, whereas the vertical (y-z) plane shows an omnidirectional pattern, represented by a circle in 2D.

According to the recognized linear scale Friis' transmission equation:

$$P_{Rx} = P_{Tx} \times G_{Tx}(\alpha) \times G_{Rx}(\alpha) \times (\frac{4\pi d}{\lambda})^{\gamma} \tag{4.1}$$

Here, α denotes the angular displacement between the Tx and Rx, and γ is the route loss exponent, as Figure shows 4.4. As the horizontal distance between the car and UAV decreases, the angle of elevation

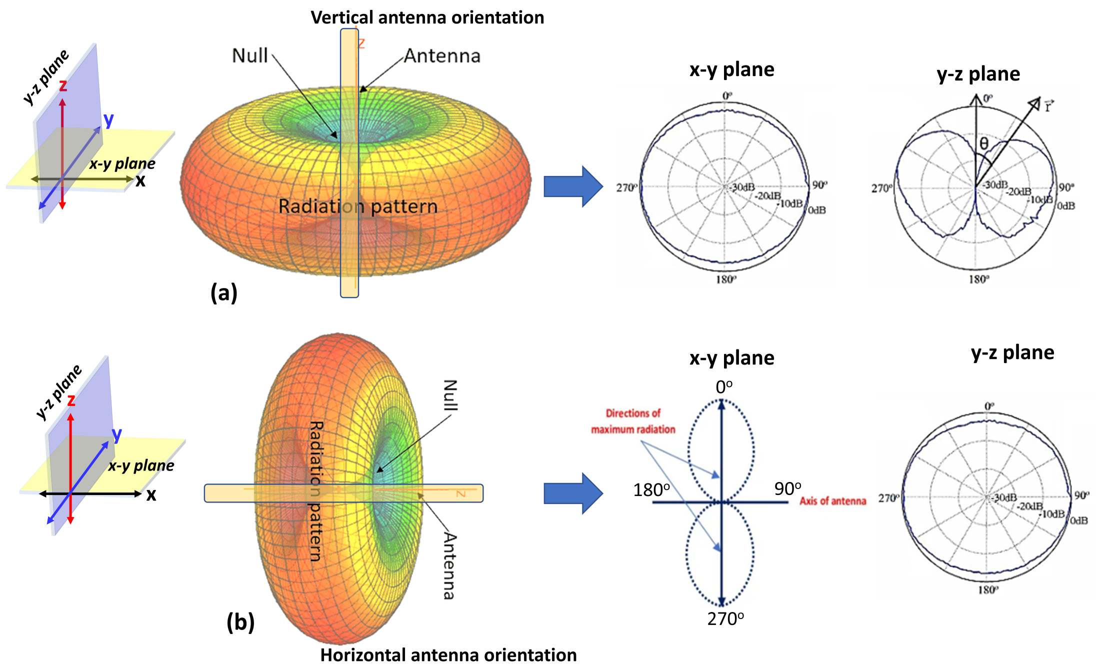

Figure 4.3: Rx and Tx Antenna Orientations and Radiation Patterns.

α between the Tx (UAV) and Rx (car) increases. As the car and UAV are positioned perpendicularly, the angle α reaches its apex, leading to alignment of the nulls (VV alignment), thereby resulting in the loss of connectivity for the vertical-vertical orientation. Consequently, it is imperative to utilize a horizontal-horizontal alignment to attain maximum gain in the LOS direction when the UAV and car are perpendicular, specifically while α equals 90°, and $\sin(90^\circ)$ equals 1 or $\cos(0)$ equals 1, since $\sin(\alpha)$ is equivalent to $\cos(90^\circ - \alpha)$.

Received Signal Modeling for LOS Scenario

The signal received at the receiving antenna for the transmitted signal $T(n)$ is often defined as the combination of the signal being transmitted with a channel impulse response, as depicted in [182]:

$$R(n) = T(n) * H(n) \tag{4.2}$$

where $H(n)$ denotes the channel's impulse response. A generalized representation of the received signal, accounting for all multipath components, can be presented as follows:

$$\begin{aligned} R_i(n) = & \frac{\lambda \Gamma_i(\theta,\phi)}{4\pi d_i} * \sqrt{G_T(\phi_i^{(TX)},\theta_i^{(TX)}) G_R(\phi_i^{(RX)},\theta_i^{(RX)})} \\ & s(n-\tau_i)\exp(\frac{-j2\phi d_m}{\lambda}|\psi_i^{TX}.\psi_i^{RX}|), \end{aligned} \tag{4.3}$$

where θ and ϕ represent the azimuth and elevation angles between the Tx and Rx, respectively, and $i = 0,1,2$ indicates the multi-path component. Γ_i indicates the reflection coefficients associated with the i_{th} multi-path component. ϕ_i indicates the polarization mismatch loss factor.The variable d represents the distance between Tx and Rx, while the variable τ_i denotes the i_{th} multi-path component's delay.

It is essential to remember that efforts have been taken to simplify the situation. Specifically, for the

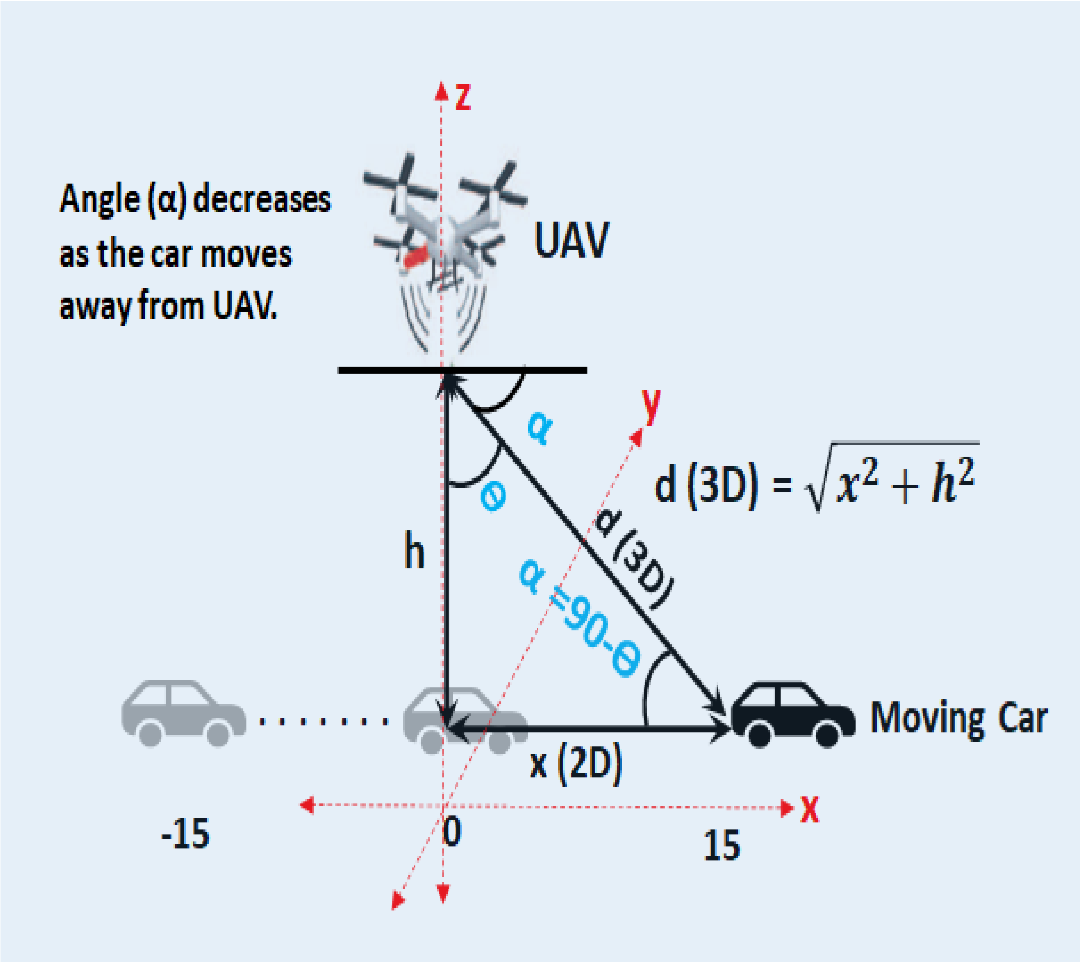

Figure 4.4: A 2D Conceptual Model of a Moving Car and a UAV.

line LOS scenario, it is assumed that the path loss exponent γ is "2", as shown in (4.1). It is believed that the coefficient of polarization mismatch value is 1 (equal to 0 dB), and any reflections caused by multipath or ground reflection are omitted in the modelling of the UAV channel. Consequently, under these assumptions, in the LOS scenario, $i = 0, \Gamma = 1, \tau_o = 0$, and $\phi_o = 1$, and G_{Tx} and R_{Tx} are linked to a sinusoidal function, we arrive at the following simple mathematical equation for the LOS component of the received signal:

$$R_o(n) = \frac{\lambda}{4\pi d_o} * \sin(\theta, \phi) * T(n). \tag{4.4}$$

We can write $P_{tx} = |T(n)|^2$ because the power level of a signal can be found using the modulus squared. The LOS component's received power can therefore be represented as follows:

$$P_{RX} = \frac{P_{TX} \sin^2(\theta) \lambda^2}{(4\pi d_o)^2}, \tag{4.5}$$

where ($\theta = \tan^{-1}(x/d)$) represents the elevation angle between the UAV and the vehicle; if the UAV is higher, this angle decreases as the vehicle moves farther away from it, or vice versa (it is noteworthy that angles θ and α exhibit inverse relationships, and our focal point is α). At the instant when the vehicle is positioned directly in front of the UAV, $\theta = 0°$, resulting in the attainment of maximum received power. However, as the vehicle aligns with the UAV, the received power is expected to reach its peak, this happens when the sinusoidal function's angle is 90 degrees, or $\alpha = 90$. By adding the actual angle α to the equation, the appropriate trigonometry angle in 4.5 becomes $\alpha = 90 - \theta$, satisfying this condition. As a result, the highest RSSI is indicated by $\sin(90^\circ - 0^\circ) = \sin(90^\circ) = \cos(0^\circ) = 1$.

4.3 Handover Mechanism Assisted by UAV

In proactive HO, a UAV is considered as a BS, CV and DL methods are used for predicting potential beam blockage. In the context of real-world wireless connectivity, predicting future obstructions poses significant challenges, as it is dependent on the velocity of the user and the environmental factors surrounding them. Our prior investigation utilized bimodal datasets (visual and wireless) for the prediction of beam obstructions, which facilitated the initiation of optimal handover processes [183]. The CV-assisted obstruction prediction is categorized into two distinct sub-tasks, namely: (i) object detection and localization (ODL), which identifies the position and classification of the obstructing entity from the images to ascertain the velocity of user's; (ii) forecasting the time to blockage (T_{blk}) utilizing the information procured from the RGB images.

In the proposed framework, the occurrence of a BLK event is triggered if both the user and the obstructing entity fall within the FoV. The main concept aims to identify the user's position and the obstruction simultaneously with the detection of the BLK event. The velocity of the user and position data are subsequently employed to compute the T_{blk}, thereby enabling the execution of proactive handover prior to any service interruption. The specifics of the proactive handover mechanism have been elaborated upon in our prior work [164]. Nonetheless, the essential steps involved in the handover process are summarized as follows:

- The BLK event is identified using the ODL algorithm, which also offers more precise location and speed data.
- The prediction of T_{blk} is carried out using the data collected via ODL.
- In the final phase, if the execution time of the handover (T_{exec}) is more than T_{blk}, the central unit (CU) performs the handover.

The minimal amount of time T_{exec} that the proposed method needs to finish a successful handover is represented. It has been divided into four components and can be mathematically expressed as follows [164]:

$$T_{exec} = T_{RGB} + T_{ODL} + T_{inf} + T_{HO}, \tag{4.6}$$

where T_{ODL} denotes the time required for object detection and localization, and T_{RGB} denotes the time required to send RGB images to the CU. The regression model's inference time is shown by T_{inf}, and T_{HO} represents the time required for the completion of the handover. Moreover, a new temporal parameter called waiting time (T_w) is introduced, with its maximum value defined as the difference between T_{blk} and T_{exec}, which is mathematically expressed as:

$$T_w^{max} = T_{blk} - T_{exec} \tag{4.7}$$

It is important to mention that each and every parameter in 4.6 are fixed, however T_w depends on T_{blk}, which is determined by the velocity and location of the user. The following key safety assumption were established in this study before getting into the details of each component:

- Wireless sensors and cameras on SBSs continuously transmit data to the CU for the real time processing.
- The ODL model correctly estimates T_{blk} and identifies the coordinates of possible obstructions; all processing is done at the CU.
- The UAV is positioned at an optimal altitude, covering the entire blocked area effectively.
- T_{blk} exceeds T_{exec}, ensuring that there is enough T_w to successfully complete the HO.

4.3.1 ODL and Prediction of Time to Block

In the context of this HO mechanism, the role of the ODL is pivotal as it accurately identifies the user's location and any potential obstructing entities. The derived location coordinates facilitate the calculation of the user's velocity. The specifics regarding the ODL's role in identifying obstruction events are not within the scope of this chapter, as they have been comprehensively addressed in preceding research [164]. To summarize concisely, The ODL procedure is divided into two main sub tasks: (i) to identify the user's pixel coordinates and any possible obstacles, using a pre-trained YOLOv3 model. (ii) To determine the user's velocity, the two-dimensional pixel coordinates generated by YOLOv3 are then translated into displacement coordinates. Because the success of the HO depends on the execution time, represented as T_{exec}, it is crucial to identify all the temporal parameters outlined in equation (4.6) to help in making a HO successful.

A neural network model that has been trained is used to estimate T_{blk} when the position coordinates and user speed are obtained from the ODL. RGB images are used to generate the dataset for the model's initial training that include the location coordinates and user velocity. To simplify the process, the blocking entity's position is kept constant while changing the user's speed and position. Although the model is trained offline, our proposed method uses real-time inference to identify T_{blk}. As indicated in the analysis from [164], the processing duration for ODL, T_{ODL}, is approximately 102 milliseconds, while the inference time, T_{inf}, is about 1 millisecond.

4.3.2 Ideal Trigger Zone and Handover Completion

The parameters of user speed, position coordinates, and T_{blk} help calculate the appropriate distance for executing the HO. The ideal trigger distance, labelled as "D," has been established through detailed analysis using a threshold distance-based framework, as expressed in the equation below:

$$D \leq S_u(T_{blk} - T_{exec}), \tag{4.8}$$

where S_u represents the known user speed, and T_{exec} is the sum of four sub-times described in equation (4.6). The analysis is conducted across various user velocities to establish the waiting time, denoted as T_w [164]. Moreover, the premature HO's effects on on the QoS are also examined. The last stage of our proposed system is the HO, wherein the parameter T_{HO} ascertains the feasibility of executing a successful handover. For the HO to be deemed successful, it is requisite that T_{blk} exceeds T_{exec}, thereby guaranteeing sufficient T_w. The T_{exec} in our case is calculated to be roughly 153 milliseconds; consequently, if the CU identifies the blocking event; T_{blk} must surpass 153 milliseconds to achieve a successful HO. In the event of adverse conditions, the user is likely to encounter a failure in connectivity if the T_{blk} is lesser than T_{exec}.

Algorithm 2: UAV-Assisted Proactive Handover Algorithm

```
Result: Decision-making and execution regarding handover
Initialisation;
BLK ← False;
Initialise S_u, L_u;
while True do
    BLK, L_u, S_u ← ODL_Module();
    if BLK then
        T_blk ← T_blk(L_u, S_u);
        T_exec ← T_exec();
        if T_blk > T_exec then
            RSSI_BS ← RSSI_BS();
            RSSI_uav ← RSSI_UAV();
            if RSSI_uav > RSSI_curr then
                Switch connection to UAV;
            else
                Maintain connection with BS;
            end
        end
    else
        Keep observing (No Handover necessary);
    end
end
```

4.4 Simulation Setup and Results Analysis

For the purpose of simulating and performing a comprehensive analysis of UAV-assisted HO, this work utilized a publicly accessible ViWi dataset [183]. The ViWi platform serves as a parametric and scalable framework for generating datasets that amalgamate visual and wireless data. This platform can generate high-fidelity synthetic datasets by combining a 3D game environment (using Blender particularly for visual data) with Wireless InSite software, which employs ray tracing methods to generate visual data. The dataset encompasses a multitude of scenarios that are contingent upon the positioning of vision sensors and the view of the user. The positioning of cameras is examined under two configurations: distributed (where cameras are positioned across multiple base stations) and co-located (where cameras are situated at a singular base station). Furthermore, with respect to the user's perspective, two distinct situations (direct visibility and obstructed visibility) are considered. Given that this investigation emphasizes proactive blockage prediction, the two scenarios have been incorporated, namely, co-located camera with direct visibility and an obstructed view. The rationale behind combining these situations is to accurately configure the dataset crucial for the blockage prediction problem.

4.4.1 Simulation Setup

The simulated framework is based on a simple scenario with one user, an obstructing object, and a UAV positioned above the obstruction zone, as illustrated in Figure. 4.1. The user pass through from the right to the left while receiving service from SBS_1. However, the potential presence of an obstructive object may disrupt the LoS communication, thereby causing a disconnection in service. Consequently, the implementation of HO is essential to prevent any service disruptions. In a prior study, a successful handover was accomplished by proactively transitioning the user from SBS_1 to SBS_2 to ensure uninterrupted connectivity. Nonetheless, this HO led in a decrease in the RSSI, that is deemed unfavourable. Therefore, to address such problem, we introduce a UAV-assisted handover approach aimed at sustaining seamless connectivity while minimizing performance degradation.

4.4.2 Impact of Channel Model on RSSI

Given that UAVs operate at diverse altitudes, it is crucial to comprehend the extent to which communication performance is influenced by signal propagation dynamics. The utilization of various channel models, which forecast the behavior of radio waves across different scenarios, constitutes the foundational basis for this comprehension. This paper offers a analysis of the comparison of the RSSI outcomes derived from two widely employed channel modeling methodologies: the Two-Ray Ground Reflection (TRGR) and the Free Space Path Loss (FSPL) model [184], assessed at varying UAV altitudes.

The investigation predominantly concentrates on the manner in which these models predict the dynamics of communication signals, which fluctuate in accordance with the UAV's altitude and the horizontal distance from the terrestrial user in UAV-to-ground contexts. The FSPL and the TRGR model represent two widely acknowledged frameworks that provide essential insights into the principles of radio frequency communication within UAV applications. The FSPL model is particularly straightforward to implement and is critical for ascertaining the fundamental attenuation of radio waves in relation to frequency and distance, as it assumes that between Tx and Rx there is a clear LOS. In the evaluation of UAV communications during high-altitude operations where the LOS component prevails, this model emerges as a vital instrument.

The following presents the path loss L in decibels:

The path loss L in decibels is given by:

$$L = 20\log_{10}(d) + 20\log_{10}(f) + 20\log_{10}\left(\frac{4\pi}{c}\right) \tag{4.9}$$

where:

- d = Distance between the Tx and Rx
- f = Signal Frequency

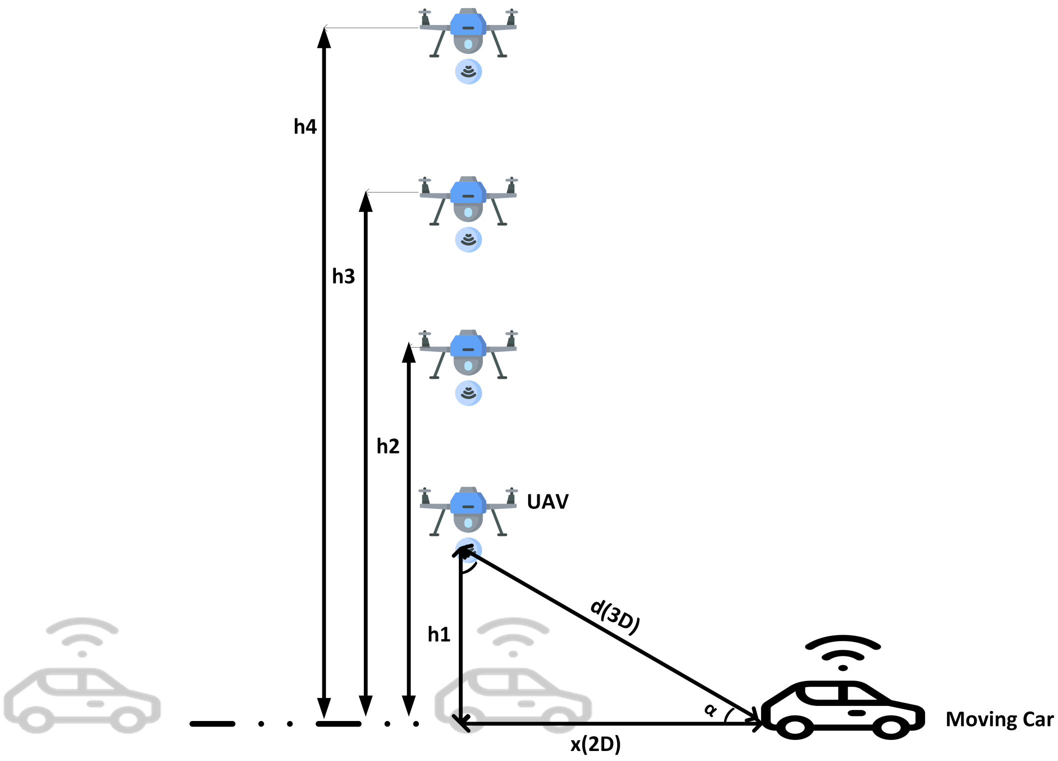

Figure 4.5: Illustration showing different UAV altitudes relative to a moving car.

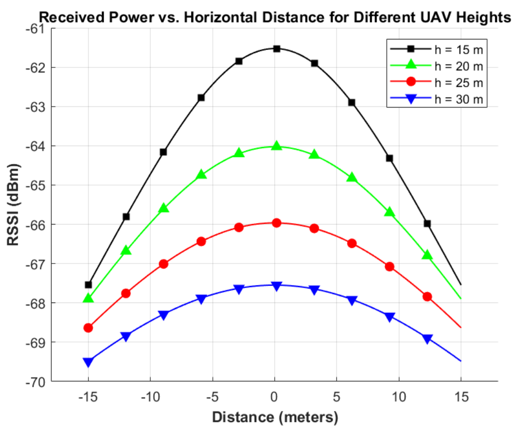

Figure 4.6: Impact of different UAV altitudes on RSSI in the FSPL model. Results are analyzed using the curve corresponding to $h = 20$ m..

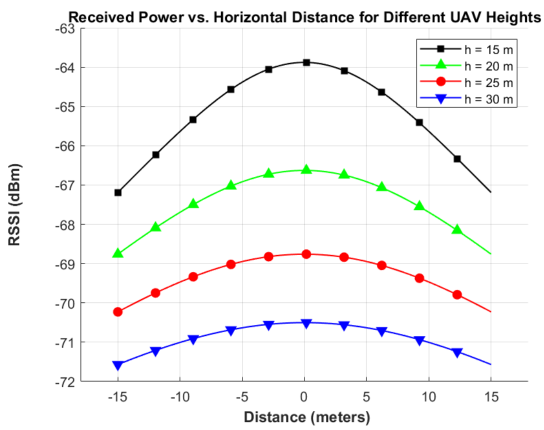

Figure 4.7: Impact of different UAV altitudes on RSSI in the TRGR model. Results are analyzed using the curve corresponding to $h = 20$ m.

- c = Speed of light

In non-logarithmic form, the received power P_r is:

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi d)^2} \tag{4.10}$$

where:

- λ = Wavelength of the signal ($\lambda = \frac{c}{f}$)

However, for low-altitude UAV operations, a more thorough analysis is provided by the TRGR model. The TRGR model, unlike FSPL, incorporates interference effects from ground-reflected paths, which vary significantly with changes in UAV altitude and user position, leading to greater fluctuations in RSSI. Understanding how ground reflections can improve or degrade the signal according to the direct and reflected channels' phase differences is crucial for understanding the connections between the surroundings and the signal that is being transmitted.

The primary challenge involved acquiring UAV channel parameters specific to mobile users. To generate UAV sample data, we integrated two different scenarios using the ViWi dataset. We used the co-located cameras with a direct view to map the RSSI according to the user's position. Using the UAV model analysis presented in Section 4.2.2, we present different RSSI values for altitudes of 15m, 20m, 25m, and 30m. Figure in 4.6 and 4.7 illustrates these results for the TRGR model and the FSPL model. When the height increases between 15 to 30 meters, the RSSI value drops from -48 to -54 db. This drop results from the fact that when the UAV's height grows, there is an impact on the antenna gain and coverage beamwidth in addition to an increase in path loss. Similarly, because of the inverse square variation in path loss with that of the distance, RSSI decreases as the horizontal distance between the UAV and the car increases. Following a thorough examination, the ViWi scenario's results were recreated at a height of 20 meters using a smooth, bell-shaped RSSI curve. As a result, after the *BLK* incident is identified, the UAV uses the RSSI of 20 meters in height as a dataset to perform HO.

The received power P_r is given by:

$$P_r = \frac{P_t G_t G_r h_t^2 h_r^2}{d^4} \tag{4.11}$$

where:

- P_t = Transmitter power
- G_t and G_r = Gains of the Rx and Tx antennas, Rx and Tx respectively
- h_t and h_r = Heights of the Rx and Tx antennas, respectively
- d = Distance between the transmitter and receiver

The following is an expression for the phase difference between the reflected and direct paths:

$$\Delta\phi = \frac{2\pi d}{\lambda} \tag{4.12}$$

where the signal's wavelength is represented by λ.

The RSSI metric exhibits a decrement for the FSPL model, ranging from -61.5 dBm to -67.5 dBm, while for the TRGR model, the RSSI reduces from -64 dBm to -71 dBm as the height escalates from 15 to 30 meters. This reduction go down due to the influence of antenna gain and coverage beamwidth, compounded by a rise in path loss associated with the UAV's elevation.

4.4.3 Findings and Analysis

The suggested system for UAV-assisted HO ensures the preservation of seamless connectivity with minimal degradation in performance. The users performance during the HO process is quantitatively assessed using the normalized RSSI metric. Initially, the user receives service from SBS_1; however, service interruption happens in the presence of a obstruction.When a Blockage (BLK) event is identified, the HO algorithm calculates the required time, represented as T_{blk}. If the execution time, T_{exec}, falls below T_{blk}, a HO request is made. The final HO is carefully completed, taking into account the correct trigger area. Within this setting, it is presumed that a UAV is situated at a designated altitude, facilitating coverage over the obstructed region.

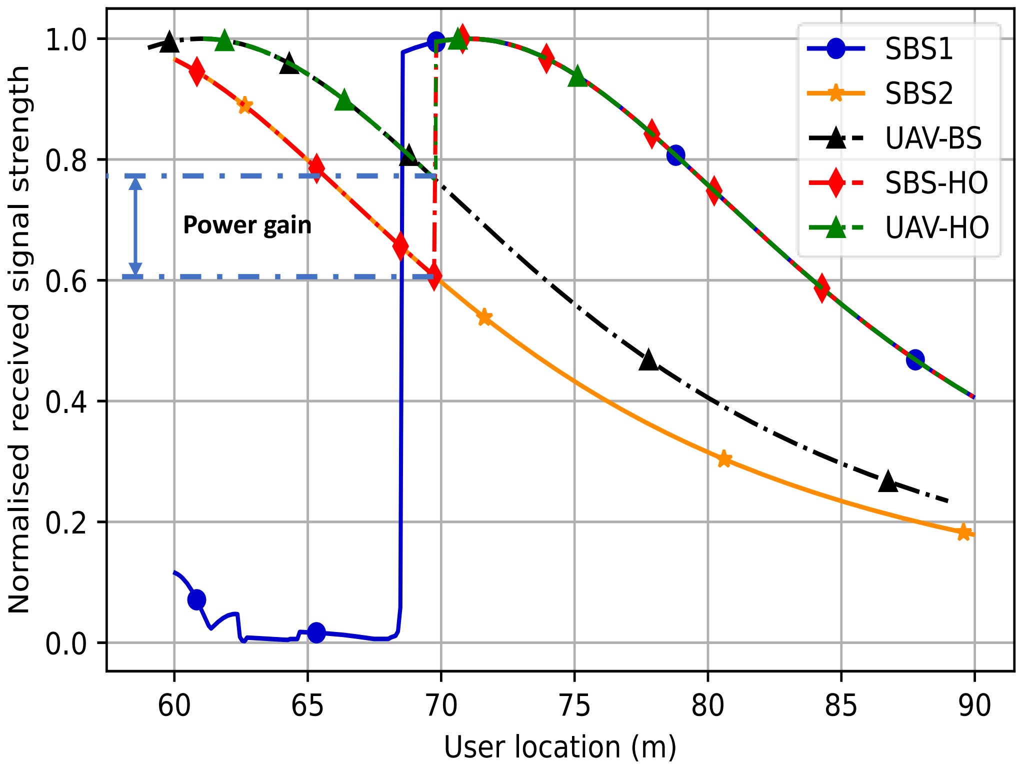

Figure 4.8: Results of UAV-assisted HO. The user is served by SBS_1 and experiences service discontinuation without HO.

The findings of the final HO is shown in Figure. 4.8. Specifically, during the optimal Handover, when the user transitions from SBS_1 to SBS_2, a considerable decrease in RSSI is noticed, which is not desirable. The decrease in RSSI is due to path loss, as SBS_2 is positioned far away from the user.

During the HO process, a UAV acts as a BS in the proposed solution. In the UAV-BS model, a decrease in the RSSI occurs due to path loss. However, despite this decrease, UAV-assisted Handover (UAV-HO) outperforms HO scenarios in general without UAV assistance. Specifically,when compared to HO scenarios without the use of a UAV, UAV-HO provides a 20% improvement in RSSI at the optimal trigger location, as illustrated in Figure. 4.8. This demonstrates how effectively using a UAV as a base station may improve user experience during the HO process.

4.4.4 Quality of Experience (QoE)

In the following section, we analyze how the PHO algorithm improves the reliability of high-frequency communication networks. This section focuses at how the PHO algorithm improves high-frequency wireless network dependability as evaluated by real-time applications that are naturally susceptible to disruption in service and latency within the network. A pertinent illustration of this scenario is the mobile user engaged in a video call, with the metric employed being the Mean Opinion Score (MOS). The MOS assess the user's QoE and is determined by human perception of the overall service quality, with scoring ranging from 1 to 5 with scores between 1 and 5 (1: bad, 2: poor, 3: fair, 4: good, and 5: excellent) [164]. The RSS values are correlated to the corresponding MOS via the reference table provided in [185]. The outcomes shown in Figure. 4.9 illustrate the comparative analysis of the MOS for both proactive and reactive handover (HO). Specifically, in the context of PHO, Fig. 4.9(a) presents the MOS for UAV-HO and Small Base Station Handover (SBS-HO). UAV-HO sustains a superior RSSI level, yielding a high MOS, except in cases where excessive UAV altitude (>30m) reduces beamforming accuracy and signal strength, as reflected by MOS dips. Conversely, in the scenario of SBS-HO, the MOS diminishes below 4 during the handover process, thereby detrimentally affecting the user's experience. Moreover, in the event of reactive HO, a disconnection in service occurs, as illustrated in Fig. 4.9(b), until a re-connection is successfully established.

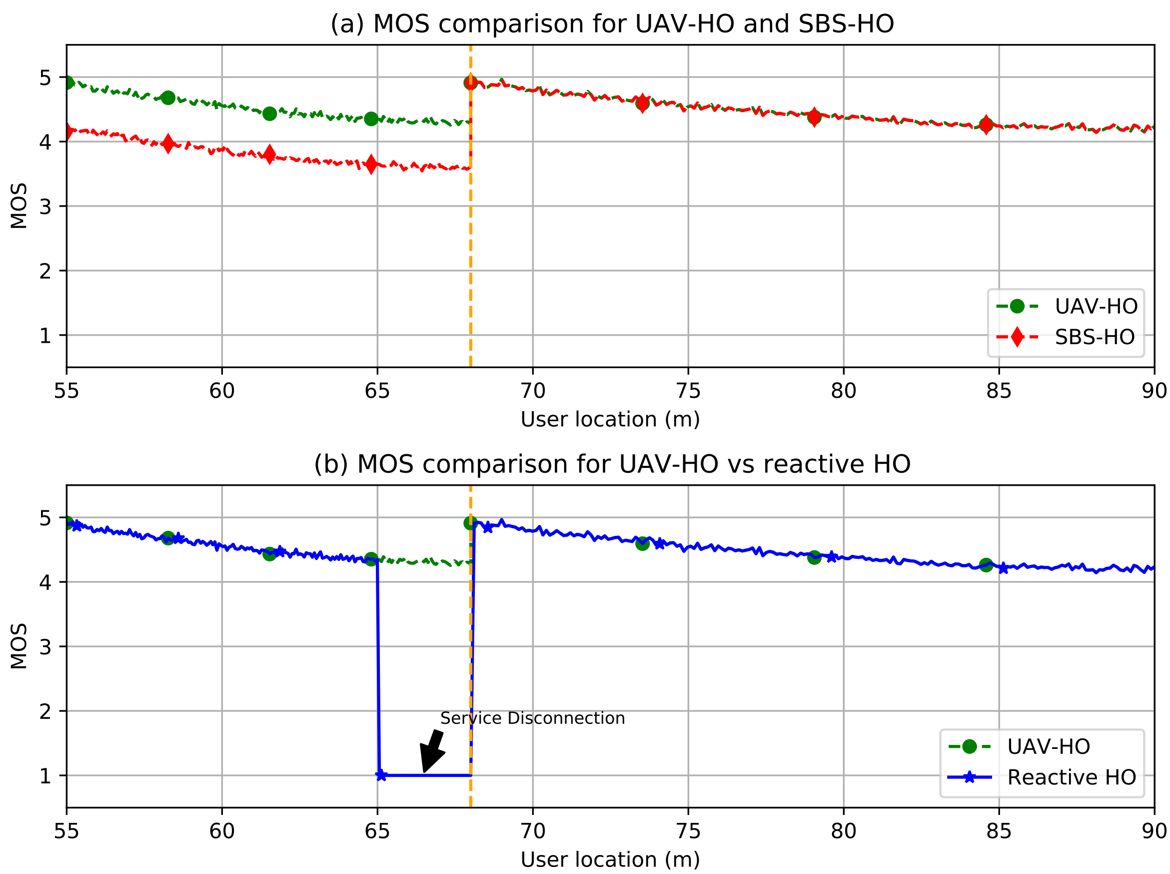

Figure 4.9: Comparison of UAV-HO, SBS-HO and reactive, measured by MOS. The users have a lower MOS when shifted to SBS_1 and experiences service disconnection for reactive H0.

4.5 Chapter Summary

This chapter discusses an innovative technique to addressing problems in MmWave communication, especially in terms of future wireless systems that require seamless communication, high speed, and low latency. The chapter focuses on the use of UAVs as dynamic BS to assist in HO processes, aiming to mitigate communication blockages caused by environmental changes and obstacles. The chapter introduces a proactive blockage prediction method that integrates CV and ML with UAV networks. This method leverages vision-based data and wireless signal information to predict potential blockages before they occur, enabling timely handovers that maintain connection quality. The UAVs act as base stations that provide alternative LoS links when primary links are disrupted, ensuring continuous and reliable communication.

A significant contribution of this work is the development of a vision-assisted, multi-modal handover framework. This framework uses Object ODL techniques to identify potential blockages and assess user speed and location. A NN model predicts the time required for HO, allowing the system to perform a proactive handover if a blockage is predicted. The use of UAVs in this context is shown to enhance overall network performance by 20%, as validated by simulation results using the Vision-based Wireless (ViWi) dataset.

The chapter also explores the modeling of UAV communication channels, considering factors such as antenna polarization and elevation angles, which are critical for optimizing signal reception in air-to-ground communication. The effect of UAV altitude and distance on signal strength is analyzed using both FSPL ans TRGR models.

This chapter concludes by emphasizing how UAV-assisted proactive handovers improve QoE, with potential applications in autonomous driving, smart cities, and disaster response. Future research could explore adaptive UAV altitude control and the integration of additional modalities like LiDAR for enhanced blockage prediction.

Chapter 5

Enhancing Latency-Aware Vision-Aided Wireless Communication in UAV-Assisted Networks: Analysing Onboard and On-Ground Training

Building on the proactive handover and blockage prediction mechanisms discussed in previous chapter, this chapter focuses on minimizing latency and cost in beam management for UAVs using mmWave and THz technologies. These technologies are essential for extending coverage, enhancing security surveillance, and supporting disaster relief operations. However, they require large antenna arrays and narrowly focused beams, posing significant challenges, particularly in maintaining effective communication links while the UAVs are in motion.

To tackle the challenge of accurately adjusting narrow beams during motiona traditionally time-consuming and resource-intensive processthis chapter introduces a novel vision-aided machine learning approach. By utilizing data from UAV cameras and wireless signals, this method efficiently predicts the optimal beam orientations, significantly reducing latency and costs associated with beam training. Building on the proactive blockage prediction mechanism discussed previously, where UAVs serve as dynamic base stations for seamless handover (HO) and enhanced connectivity, this chapter integrates advanced vision-based learning for more precise beam management. Previously, a proactive blockage prediction mechanism was introduced, using CV to detect potential obstacles, location and speed of the user ensuring seamless connectivity and enhancing network performance by 20%. The current chapter extends this framework by incorporating on-device inference capabilities, reducing dependency on ground-based processing.

The proposed vision-aided beam management method was evaluated on an extensive dataset comprising visual and wireless communication data from UAVs and ground communication infrastructure. The results indicates that the Mobilenet-based approach achieves approximately 88% accuracy in predicting the best beam direction for the top-1 prediction and nearly 100% accuracy for the top-3 predictions. Additionally, performing these computations directly on the UAV (on-device inference) significantly reduces communication delays by 13% and lowers communication costs by 49% compared to on-ground inference.

These studies emphasize the practical advantages of the proposed machine learning approach in managing highly mobile mmWave/THz UAV communications effectively. By improving the precision of beam orientations and reducing the latency and costs associated with beam training, this research contributes to the development of more reliable and efficient communication systems for UAVs, ultimately enhancing their operational capabilities in various critical applications. The integration of advanced vision-aided techniques in beam management highlights the potential of UAVs equipped with mmWave/THz technologies to transform wireless communication landscapes, particularly in scenarios demanding high mobility and rapid adaptability.

5.1 Introduction

The widespread use of wireless technology has led to a significant increase in congestion in the low-frequency RF bands. Therefore, it has become apparent that moving into higher frequency ranges is crucial to ensure high transmission speeds and wide bandwidth. This shift is necessary to meet the growing demand for data transmission [153, 186]. As a result, communication in the millimeter-wave (mmWave) spectrum and higher frequencies has gained interest from academia and industry [187]. On the one hand, UAVs can serve as aerial communication platforms, such as relays, base stations, and data aggregators. This enables them to offer communication services when needed for ground-based users or expand the coverage area of established terrestrial cellular networks. This approach is known as UAV-assisted wireless communications [188]. On the flip side, UAVs can also be incorporated into cellular networks as new aerial users, carrying out functions such as goods delivery, aerial surveillance, monitoring, remote sensing, and so forth. This is performed through interaction with the terrestrial base stations [128]. Given their potential applications, UAVs present numerous challenges such as planning trajectories and paths, avoiding collisions, controlling mobility, addressing cost and security concerns, managing data offloading, dealing with latency, and optimizing energy consumption [189]. The design of UAV trajectories, resource distribution, and the inherent delay associated with the communication link between UAVs and ground users are some of the elements that affect latency in UAV-assisted networks. In order to reduce latency and improve overall network performance, it has been determined that optimizing UAV trajectory and communication strategies are crucial [190]. Article in [191] focus on the use of UAVs as base stations for wireless communication with the objective of energy management. Instead, the researchers adopt a new strategy in which the UAVs land on designated areas called landing stations and save energy by not to simply flying around or hovering in the air, waiting for any new tasks. Lastly, network-level performance was analytically evaluated via a mathematical model in the paper, which demonstrated that a significant amount of energy can be saved to UAVs with only a negligible degradation of coverage and throughput.

Although UAV-assisted networks have great potential, current approaches frequently fail to effectively address the latency problem. This is mainly because of the complex connections between UAV mobility, communication dynamics, and the varying demands of ground users. For example, trajectory design for multiple-UAV aided wireless networks needs to take into account the interference between UAVs as well as the spatial-temporal dynamics of user demand, as these factors can have a substantial impact on the network's latency and throughput [192]. Comparably, in order to satisfy the Quality of Service (QoS) criteria, including latency, of various applications, the distribution for resources, such as bandwidth and power, must be carefully handled [193].

Millimeter wave (mmWave) technology, when combined with UAVs and cameras, offers a novel solution to tackling issues in wireless communications and object identification, particularly in autonomous systems. This integration primarily aims to improve the accuracy and effectiveness of beam prediction, blockage prediction, and self-localization in complex scenarios. Deep learning techniques, such as convolutional neural networks (also known as CNNs) and recurrent neural networks (RNNs), are critical in processing visual input from UAVs for wireless communication purposes. For example, adapting pre-trained ResNet-18 models for beam and blockage prediction demonstrates the potential of transfer learning to leverage existing architectures for new tasks [194][195]. These models are fine-tuned using images labeled with matching beam indices, providing a successful way of image-to-beam indices classification.

In this regard, our work presents a framework that combines the state-of-the-art MobileNet architecture with a vision-assisted beamforming system for UAV. This integration enhances the UAV's ability to make decisions in real-time based on visual inputs by utilizing MobileNet's effective convolutional neural network (CNN) design, which is designed for mobile and embedded vision applications. Due to this, UAVs are able to dynamically modify their beamforming strategies in order to maximize communication linkages with ground users, taking into account factors like user density, terrain, and obstacles that might affect signal quality. This new method makes a substantial contribution to the field of UAV-assisted wireless communication by improving adaptive communication, increasing network efficiency, reducing latency, while encouraging energy efficiency. This research leverages lightweight MobileNet architectures to achieve real-time beamforming, addressing limitations in prior vision-aided methods such as high latency and computational overhead.

5.2 Related Work

To fully capitalize on the era of the Internet of Everything (IoE), a strong communication infrastructure is required that supports low latency and high reliability. Hence, the introduction of 5G technology has brought about the idea of URLLC as a major performance indicator [196]. According to [197], wireless communication technologies such as 5G Advanced and 6G are expected to handle highly mobile devices like UAVs and autonomous vehicles in the coming years. Drones, also known as UAVs, are considered crucial in driving future technological advancements. They can help extend the range of mmWave wireless networks, enable low-latency applications, and enhance security surveillance systems. These UAV-linked mmWave wireless networks can be split into two groups, The first group involves using UAVs as aerial Access Points (APs) or relays to improve the performance of the ground-based cellular network. The second group involves UAVs operating as aerial User Equipment (UEs) connected to the terrestrial cellular network. In situations that require quick communication responses, such as emergencies or hotspot areas, UAVs can serve as aerial APs, establishing temporary data connections with ground users. This is one of the most popular communication scenario for UAV-assisted cellular networks [198]. Using UAVs has improved wireless communication by establishing direct connections between the air-

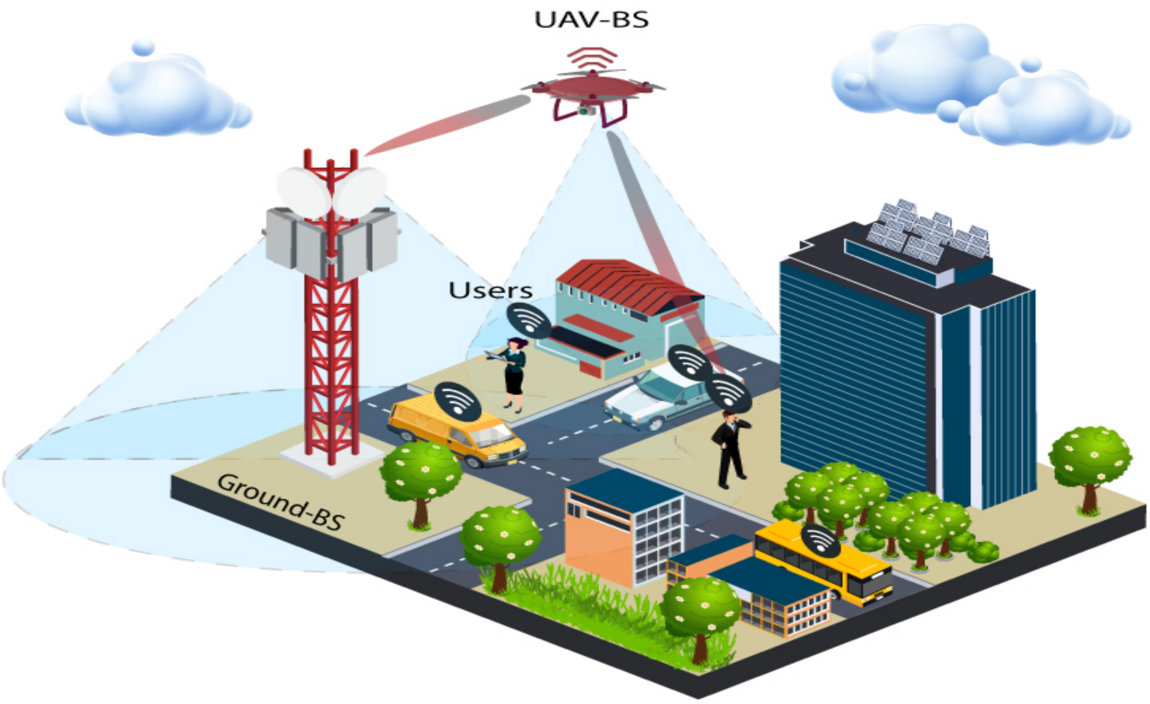

Figure 5.1: UAV as a Mobile Base Station in an Urban Environmen

borne and ground-based components (AtG). This innovation has reduced signal loss during transmission and improved the QoS for these connections. Moreover, the mmWave communication technology has shown remarkable effectiveness in situations characterized by emergencies, unfamiliar terrain, or dynamic topological environments[153]. UAVs are expected to have mmWave/THz transceivers to meet the high data rate requirements of modern applications [172]. This is because mmWave/THz communication systems provide a large bandwidth. However, these systems need extensive antenna arrays and use narrow beams to maintain a good signal-to-noise ratio (SNR). Choosing the most suitable beams in high-frequency systems with large antenna arrays involves significant overhead in beam training.

Latency-aware communication in UAV networks have gained a lot of interest because of their critical significance in real-time applications including emergency response and traffic control. Researchers have investigated several ways to reduce latency, such as optimizing UAV flight patterns and developing efficient data routing systems. Mozaffari et al. [22] investigate techniques for optimizing UAV deployment and resource allocation to improve network performance while maintaining low latency. Zou et al. proposed a vision-assisted 3-D predictive beamforming architecture that provides a substantial advancement in UAV communications. It offers a practical solution to the issues provided by high mobility and energy constraints, opening the way for more efficient and effective UAV-to-vehicle communication systems [199].

The application of computer vision and deep learning in wireless communication, notably in UAV networks, has shown potential in terms of enhancing signal transmission model accuracy and beamforming algorithms. Therefore, the use of AI techniques for computer vision in UAV networks attempts to enhance beam alignments and blockage prediction, which are critical for mmWave communications. Alzenad et al. investigate how UAVs equipped with cameras can utilize visual information to predict ideal communication beams and identify potential blockages, hence increasing mmWave communication reliability [200]. Charan et al. developed a machine learning system that uses images taken by the UAV's cameras to determine the optimal beam index for the mmWave signal [147]. Notably, another study provides a multi-modal machine learning architecture that combines positional and visual data to improve beam prediction. This approach takes advantage of the synergy between GPS data, camera pictures, and mmWave beam training datasets to improve the accuracy of beamforming decisions in dynamic situations [100]. Similarly, Zarei et al. utilize a Squeeze-and-Excitation ResNet50 (SE-ResNet50) model to demonstrate a unique method for reducing beam training overhead in UAV-enabled mmWave communications. The SE network prioritizes useful features through channel-wise feature recalibration, allowing it to adapt to changing conditions and maximize predictions across several scenarios. This solution uses visual data captured by UAV-mounted cameras to improve the accuracy of beam prediction in dynamic scenarios [201]. Building on this, another study proposed a vision-assisted beamforming framework tailored to millimeter-wave (mmWave) communications. Their approach takes advantage of the inherent vision functionality of UAVs to assist beamforming, lowering the overhead caused by frequent beam tracking updates in high mobility conditions. The proposed framework detects vehicles using a YOLO-based deep learning network and guides the beamforming process based on the positions discovered. Experiments and simulations on the UAVDT dataset demonstrated notable performance gains in terms of received signal-to-interference-plus-noise ratio (SINR), emphasizing the efficiency of integrating visual information for beam prediction in UAV-to-vehicle connections [202].

5.3 Methodology

This research explores a communication system deployed in a bustling downtown scenario. The primary components of the system include a millimetre-wave (mmWave) base station, mobile users, and a UAV designed to operate in dynamic urban environments.A classic cellular tower (Ground-BS) operates as a typical base station, providing a wide-area signal. This highlights its importance in enabling broad cellular connectivity. In contrast, the UAV (UAV-BS) can be used as a mobile base station to dynamically improve network capacity and coverage, which is especially advantageous in highly populated or difficult-to-reach places as shown in figure 5.1. This configuration indicates a flexible and adaptable communication network capable of addressing high data demands while maintaining reliable connectivity in a variety of urban areas. The base station, strategically located to optimize coverage, communicates directly with a flying UAV. This model is pivotal in understanding the real-world applications and challenges of mmWave communications in urban settings.

5.3.1 System Elements

Basestation: At the heart of this system is a basestation equipped with an M-element ULA. This configuration allows for advanced directional beamforming capabilities, crucial for mmWave communication's high-frequency spectrum.

UAV: The recipient of the basestation's signal is a uniquely designed UAV. It carries a single-antenna mmWave receiver, enhancing its receptivity to the basestation's signal. Additionally, it is equipped with three RGB cameras, an innovative feature that enables the UAV to capture comprehensive data about the surrounding wireless environment. The UAV's RGB cameras provide high-resolution visual data critical for environmental analysis, enabling the detection of obstacles and user density for adaptive beamforming decisions.

Users: The network users comprise a diverse group, each equipped with advanced mobile devices. Every individual carries a versatile smartphone, enhancing connectivity to both terrestrial and UAV base stations. These devices also feature high-resolution cameras, allowing users to capture and share high-quality photos and videos. Moreover, sensors on these smartphones provide extensive environmental data, facilitating augmented reality applications and improved situational awareness.

5.3.2 Signal Propagation

The communication between the basestation and the UAV leverages OFDM with K subcarriers. This approach is beneficial for handling the high bandwidth requirements of mmWave communication. Furthermore, a cyclic prefix of length D is employed to mitigate inter-symbol interference, a common challenge in urban communication scenarios.

5.3.3 Signal Reception and Processing

The UAV's received signal, $y_k[t]$, is modeled as $y_k[t] = h_k^T[t] f_q[t] x + v_k[t]$, where $f \in F$ represents the best beamforming vector at time t, and $v_k[t]$ is a noise sample from a complex Gaussian distribution $\mathcal{N}(0, \sigma^2)$. The transmitted complex symbol $x \in \mathbb{C}$ follows the power constraint $\mathbb{E}[|x|^2] = P$, where P represents the average symbol power.

5.3.4 Beamforming Vector Selection

Selecting the beamforming vector, $f^*[t]$, at each time step is crucial for maximizing the average receive SNR.

The formula is $f^*[t] = \arg\max_{f_q[t] \in F} \frac{1}{K} \sum_{k=1}^{K} SNR |h_k^T[t] f_q[t]|^2$, where SNR is the transmit signal-to-noise ratio, $SNR = \frac{P}{\sigma^2}$.

5.3.5 UAV Trajectories and Data Samples

UAV Specifications: The UAV, central to this dataset, is equipped with three cameras oriented in different directions, enabling a comprehensive visual coverage of the street. The visual data range spans the x-axis from -100 to 300 meters. Additionally, the UAV features a half-wave dipole receiver antenna for precise wireless data acquisition.

Basestation Configuration: Two basestations are positioned precisely 100 meters apart on either end of the main street. Each station has a half-wave dipole antenna array oriented along the z-axis, with 128 antennas extending along the x-axis.

Trajectory Modeling: The dataset comprises 6,735 samples, representing 17 distinct UAV trajectories. These trajectories, primarily varying in the x and y-axes, maintain a constant altitude of 50 meters. The UAVs' linear paths, either in the positive or negative x direction, are meticulously designed above the street, with y-axis variations from -5.625 to 1.875 meters.

Onboard Training and Testing: The Mobilenet model is trained and tested directly on the UAV. This approach is instrumental in handling the computational constraints typical of UAV platforms, thereby optimizing the system's overall efficiency. By processing data onboard, the system minimizes latency, which is critical in dynamic urban environments.

Data Transmission and Beam Prediction: In a significant departure from traditional methodologies, only the inference data, rather than the entire data set, is transmitted back to the basestation for beam prediction. This strategy substantially reduces the volume of data that needs to be transmitted, further minimizing latency and enhancing the responsiveness of the communication system. The efficient prediction of the optimal beamforming vector is vital for maintaining robust and reliable mmWave communications between the basestation and the UAV.

5.4 System Model and Problem Formulation

In this study, we consider a mobile communication system where a mmWave base station, equipped with a N-ULA, communicates with a high-mobility UAV. The UAV is equipped with a single-antenna mmWave receiver and an advanced visual sensor array, primarily an RGB camera. This setup captures real-time environmental data crucial for beamforming vector selection.

The transmission employs OFDM with J subcarriers. A predefined beamforming codebook, $\mathbf{B} = \{\mathbf{b}_m\}_{m=1}^{M}$, where $\mathbf{b}_m \in \mathbb{C}^N$, is utilized to facilitate communication. The downlink channel on the j-th subcarrier at time t is represented by $\mathbf{g}_j[t] \in \mathbb{C}^N$, and the noise is modeled as a sample from a complex Gaussian distribution $n_j[t] \sim \mathcal{N}_{\mathbb{C}}(0, \sigma^2)$.

The received signal on the j-th subcarrier at time t is defined as:

$$y_j[t] = \mathbf{g}_j[t]^\dagger \mathbf{b}_m x + n_j[t] \tag{5.1}$$

where x is the transmitted symbol adhering to the power constraint $|x|^2 = P$. The objective is to maximize the SNR, which is given by:

$$\mathrm{SNR}_j[t] = \frac{|\mathbf{g}_j[t]^\dagger \mathbf{b}_m|^2 P}{\sigma^2} \tag{5.2}$$

To address the challenge of dynamic beam selection without direct channel state information, we propose using a MobileNet-based architecture due to its efficiency in processing high-dimensional image data onboard. The UAV's camera captures RGB images $V[t] \in \mathbb{R}^{W \times H \times 3}$, which serve as the input to our predictive model.

Machine Learning Model for Beam Prediction

The predictive model M, parameterized by θ, aims to estimate the optimal beamforming vector from the image data. The training dataset D comprises image-beam pairs (I_i, B_i) for $i = 1, 2, \ldots, |D|$. The model minimizes the loss function L, which measures the prediction error against the ground truth beam information:

$$\theta^* = \arg\min_{\theta} \frac{1}{|D|} \sum_{i=1}^{|D|} L(M(I_i; \theta), B_i) \tag{5.3}$$

Post-training, the optimized model is employed for real-time inference to predict the beam information $\hat{B}_{\text{new}}$ from a new image I_{new}:

$$\hat{B}_{\text{new}} = M(I_{\text{new}}; \theta^*) \tag{5.4}$$

5.5 Proposed Vision Assisted Lightweight Beam-forming Framework

Our proposed framework integrates the cutting-edge MobileNet architecture into a vision-assisted beamforming system for UAV networks as shown in figure 5.2. This integration is engineered to exploit the lightweight and efficient nature of MobileNet, enabling high-performance on-device vision processing within the constraints of edge computing.

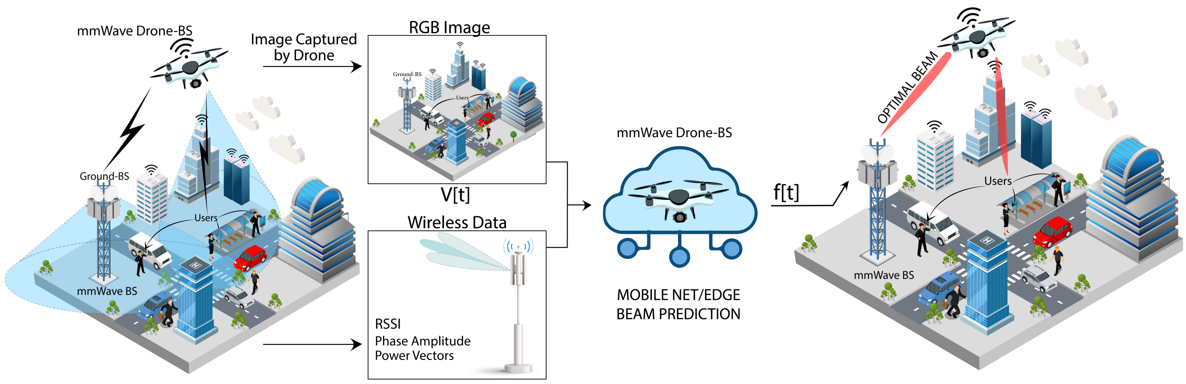

Figure 5.2: Schematic of the Proposed Vision-Assisted Beamforming Framework in UAV Networks, leveraging MobileNet for real-time edge computing. The system captures high-resolution vision data, which is processed on-board using the MobileNet architecture for swift feature extraction. This data informs an inference model that dynamically adjusts the UAV's beam direction for optimal communication efficiency and robustness.

At the core of our framework is a UAV equipped with high-resolution cameras, tasked with the collection of real-time visual data from its operating environment. This visual data is pivotal for the beamforming mechanism, providing a rich context that includes dynamic object detection, environmental analysis, and spatial orientation. To process this influx of vision data, we employ the MobileNet model, renowned for its efficiency in handling high-fidelity images with a minimal computational footprint. MobileNet's architecture leverages depthwise separable convolutions, drastically reducing the model size and computational complexity. This design choice is instrumental in facilitating on-board processing, eliminating the need for data offloading to centralized servers, and thereby reducing latency significantly.

The UAV's computational unit is augmented with edge computing capabilities, ensuring immediate processing of the captured vision data. The integration of MobileNet into this unit enables the extraction of relevant features directly on the UAV. The model's compact structure is optimized for the limited computational resources available on UAVs, ensuring that real-time processing demands are met without compromising the efficacy of the data analysis.

The processed data, rich with environmental context, feeds into an advanced inference model that underpins the beamforming process. This model harnesses machine learning algorithms to predict the most effective beam orientation, ensuring robust and optimal communication links. The real-time inferencing capabilities provided by MobileNet allow for dynamic adjustment of beam parameters, responding to the continuously evolving conditions captured by the UAV's cameras.

In the final stage of our framework, the output from the inference model is utilized for intelligent beam management. The UAV's communication system employs this information to adaptively shape and steer the communication beam, enhancing signal quality and strength towards targeted receivers. This adaptive mechanism is critical for maintaining high-quality communication channels in complex and changing environments, such as urban landscapes or during disaster response operations. By leveraging the MobileNet architecture within this UAV-based system, we enable a new paradigm for real-time, on-device processing, critical for the next generation of intelligent UAV networks.

Algorithm 3: Vision-Assisted Beamforming Using MobileNet

```
Data: UAV Camera, Edge Compute Unit, Inference Model, Comm System, Wireless Data
Result: Optimal Beam Direction
Initialize UAV system with MobileNet and Inference Model on Edge Compute Unit;
while UAV is in operation do
    Capture Image ← UAV_Camera.capture();
    Collect Wireless Data ← Comm_System.collect_wireless_data();
    Processed Features ← Edge_Compute_Unit.process(Capture_Image, Wireless_Data,
      MobileNet);
    Beam Prediction ← Inference_Model.predict(Processed_Features);
    Optimal Beam Direction ← determine_optimal_direction(Beam_Prediction);
    Comm_System.adjust_beam(Optimal_Beam_Direction);
    if environmental changes detected then
        goto capture_image;
```

The step by step explanation of our proposed vision assisted beamforming algorithm is stated as follows:

1. The UAV system is initialized with MobileNet, a pre-trained convolutional neural network Model deployed on the Edge Compute Unit (UAV). This setup includes configuring the UAV camera, the communication system, and loading the necessary machine learning models. This ensures the system is ready to capture, process, and infer data in real-time.

2. The main loop begins and continues to run as long as the UAV is operational. This loop ensures continuous data capture and processing.

3. The UAV camera captures an image of the surrounding environment. This visual data provides contextual information that can be used to enhance the beamforming process.

4. Concurrently, the communication system collects wireless data, including signal strength, interference levels, and other relevant metrics.

5. The captured image and the collected wireless data are sent to the Edge Compute Unit. Here, MobileNet processes the image to extract features, while the wireless data is preprocessed and combined with the image features.

   This step leverages the computational power of edge devices to perform complex data processing tasks close to the data source, reducing latency and improving response times.

6. The processed features are fed into the Inference Model, which predicts the optimal beam direction. The model has been trained to interpret the combined features and provide accurate beam orientation predictions.

7. The predicted beam direction is analyzed to determine the optimal beam orientation. This step involves evaluating the models output to ensure it aligns with the current environmental conditions and communication requirements.

8. The communication system adjusts the beam orientation based on the determined optimal direction. This adjustment ensures that the communication link maintains high quality and reliability.

9. The system continuously monitors for any environmental changes that may impact beam orientation. This includes detecting obstacles, changes in signal interference, or any other factors that could degrade communication quality.

5.5.1 Utilization of the ViWi Framework

The research leverages the publicly available ViWi framework [148], specifically tailored to create the ViWi-Drone scenario[147]. This rich dataset uniquely combines wireless and visual data, integral to the study. Each data sample encompasses an RGB image paired with a corresponding beam index. These samples are products of a detailed simulation, replicating a dynamic downtown street scene with multiple moving objects. This approach differs notably from the ViWi-BT scenario, as the user in the ViWi-Drone dataset is a UAV positioned at a 50-meter altitude.

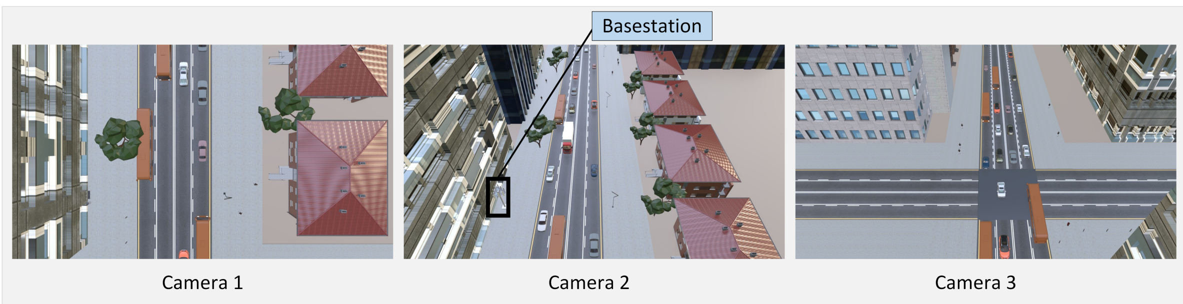

Figure 5.3: The diagram illustrates the various sections of the street as recorded by the three cameras at a specific moment and depicts the two base stations, BS1 and BS2, as observed by cameras 2 and 3, respectively. These images are sourced from the ViWi_Drone Dataset.

5.5.2 Data Handling and Scenario Modeling

Dataset Division: The data samples are categorized into two main groups for in-depth analysis: (i) The BS1 scenario, consisting of image and beam pairs exclusively from basestation 1, and (ii) The BS2 scenario, comprising samples from basestation 2 only.

Training and Validation Sets: For each scenario (BS1, BS2, and the combined scenario), the dataset is segregated into training and validation sets, adhering to a 70-30% split. This division facilitates a robust training regime while ensuring comprehensive validation of the model's efficacy.

5.5.3 Model Training and Validation

DL Mobilenet Implementation: To enhance the efficiency and reduce latency in the communication system, the UAV or drone is equipped with DL Mobilenet for onboard processing. This deep learning model is a crucial component for real-time data analysis and decision-making in the UAV's operation. Mobilenet's lightweight architecture makes it an ideal choice for onboard computational tasks, offering a balance between performance and computational overhead. The hyperparameters used to fine-tune the model are listed in Table 5.1. The proposed framework is trained using a Tesla T4 GPU provided by Google Cloud Platform.

Table 5.1: Training Parameters

Training Parameter	**Value**
Batch Size	64
Learning Rate	1×10^{-3}
Learning Decay	1×10^{-4}
No of Epochs	40

5.5.4 Performance Evaluation

Beam Prediction Accuracy

This study addresses beam prediction as a binary classification problem. Accuracy serves as the main performance indicator, representing the proportion of correct predictions to all predictions made. Nonetheless, depending exclusively on accuracy can be deceptive due to the accuracy dilemma. This dilemma occurs when a model achieves high accuracy mainly by predicting the majority class in an imbalanced dataset, thereby missing the genuine patterns within the data.

To provide a more comprehensive evaluation, additional metrics such as precision (specificity), recall (sensitivity), and F1-score are considered. These metrics are defined as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5.5}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5.6}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5.7}$$

where TP denotes true positives, FP denotes false positives, and FN denotes false negatives.

Latency and Communication Cost

UAV systems transmit large amounts of raw visual data to a base station. Due to the immense volume of data and the fundamental limitations of communication channels, this data transmission, especially via wireless networks, can introduce significant latency. Since there is no longer a requirement for the data to travel between the UAV and the ground station, we can completely eliminate these transmission delays by integrating MobileNet directly on the UAV. This method makes sure that data processing happens on the UAV in real time by taking advantage of MobileNet's ability to process images efficiently even when the UAV's onboard computer capabilities are limited. The proposed approach utilizes on-device inference, resulting in a considerable reduction in beam prediction inference latency. This study considers a camera frame rate of 26 frames per second (fps) and a mmWave backhaul link operating at 10 Gbps [180].

The total inference latency, L_{total}, is a cumulative measure calculated as follows:

$$L_{\text{total}} = T_{\text{capture}} + T_{\text{transmit}} + T_{\text{inference}} \tag{5.8}$$

The energy efficiency of the proposed model is assessed based on two primary factors: the computation time needed for local training and the transfer of parameters during each communication round. This efficiency metric is expressed mathematically as follows [203]:

$$E_{\text{eff}} = E[(\kappa \times t_{\text{comp}}) + (\delta \times P_{\text{transfer}})] \tag{5.9}$$

In this equation, κ is the computation constant with units of energy per second, and δ is the communication constant with units of energy per kilobyte. E denotes the number of epochs, t_{comp} is the computation time which varies with the device type, and P_{transfer} represents the size of the parameters transferred in each communication round. For the sake of simplifying our analysis, the constants κ and δ are set to 0.003 and 0.0001, respectively, as referenced in [203].

5.6 Results and Analysis

This section presents the performance evaluation of the MobilenetV2 model based on different evaluations, for example, beam prediction accuracy, latency, and received power for scenarios BS-1 and BS-2.

5.6.1 Beam Prediction

In this study, beam prediction is approached as a binary classification problem. Therefore, accuracy is used as the primary metric to evaluate performance, representing the proportion of correct predictions among all predictions made. this study evaluates the efficacy of different MobileNet architecturesMobileNet_V1, MobileNet_V2, and MobileNet_V3in predicting the optimal beam direction as a binary classification task. The average Top-1, Top-2, and Top-3 accuracies for two diferent base staion BS1 and BS2 serve as metrics for assessment, denoting the probability that the correct beam direction is within the top N predictions made by the model. The results are compared with the baseline Resnet-18 presented in [147].

Table 5.2: Top-k Beam Prediction Accuracy for BS1

Model	**Top-1 Beam Prediction Accuracy**	**Top-2 Beam Prediction Accuracy**	**Top-3 Beam Prediction Accuracy**
Mobilenet V1	58%	67%	74%
Mobilenet V2	89%	94%	97%
Mobilenet V3	92%	98%	99%
Resnet-18	92%	99%	99%

The results for BS1 and BS2 beam prediction accuracy are shown in figure 5.4 and 5.5 respectively. The initial version, MobileNet_V1, demonstrates moderate predictive accuracy. With an average Top-1 accuracy of 58%, the model correctly identifies the optimal beam direction less than half the time on the first prediction. However, the accuracy improves to 67% and 74% for Top-2 and Top-3 predictions, respectively for BS1. This increment indicates that while MobileNet_V1 may not often predict the optimal beam direction initially, the correct prediction is likely within its first three guesses. This level of performance may be suitable for non-critical applications where delays in achieving the optimal communication link can be tolerated. The figure in 5.4 depicts the beam prediction accuracy for MobileNet_V2 for BS-1 as well. The figure shows the top1, top2, and top3 beam accuracy. It is observed from the figure that the top 1 accuracy for BS-1 is more than 89%. It means that the proposed lightweight model predicted the top1 beam with 89% accuracy. The performance improves further when we consider top3 and top5 beam accuracies. The results show that, while ResNet-18 excels at Top-1 accuracy, MobileNet models, particularly V2 and V3, perform comparably or better in Top-2 and Top-3 accuracies. This shows that, while ResNet-18 is best suited for applications that need high precision, MobileNets provide greater flexibility and reliability, constantly placing the correct beam among the top predictions. This feature is useful in dynamic or resource-constrained contexts where a balance of accuracy and computing efficiency is required. The beam prediction accuracies for BS1 and BS2 are presented in 5.2 and 5.3 respectively.

Table 5.3: Top-k Beam Prediction Accuracy for BS2

Model	**Top-1 Beam Prediction Accuracy**	**Top-2 Beam Prediction Accuracy**	**Top-3 Beam Prediction Accuracy**
Mobilenet V1	57%	66%	74%
Mobilenet V2	88%	97%	98%
Mobilenet V3	90%	98%	99%
Resnet-18	90%	97%	99%

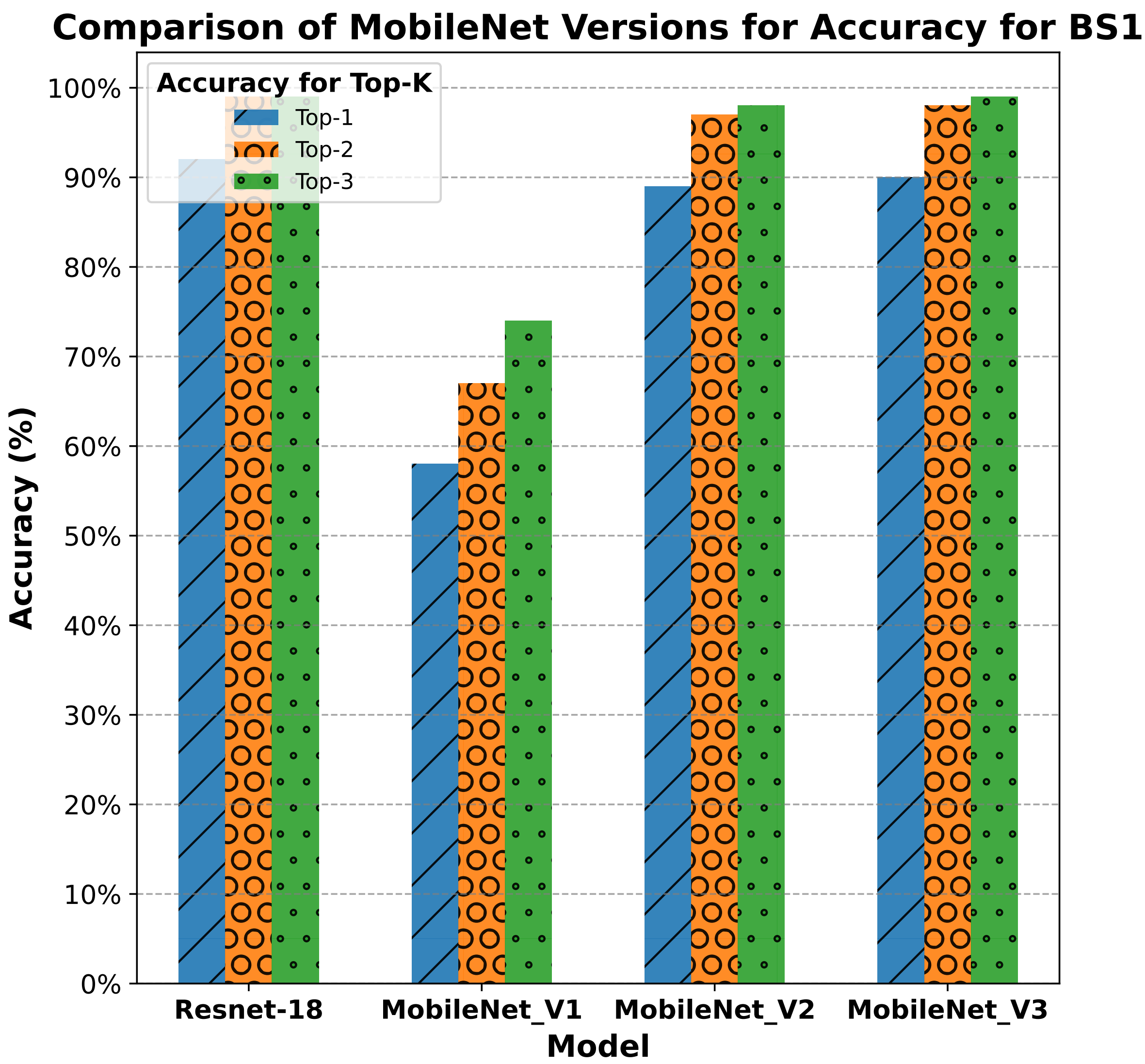

Figure 5.4: This figure depicts the top-k (k = 1, 2, 3) beam prediction accuracies of the proposed lightweight beam prediction model. The picture compares the top-k accuracies of various MobileNet models with the baseline ResNet-18 model for Base Station 1 (BS1).

We additionally presented the precision, recall, and F1 scores for the Mobilenet models under both scenarios, BS1 and BS2, to further confirm the efficacy of our proposed method. The precision achieved was 0.6425647, recall was 0.66445696, and the F1 score reached 0.83048433 for the top1 beam prediction. These findings are detailed in Table 5.5.

Table 5.4: Performance Metrics for MobilenetV2 and Resnet-18 in Scenarios BS1

Scenario	**Precision**	**Recall**	**F1 Score**
MobilenetV2	0.898671	0.882042	0.880208
Resnet-18	0.877772	0.871358	0.869700

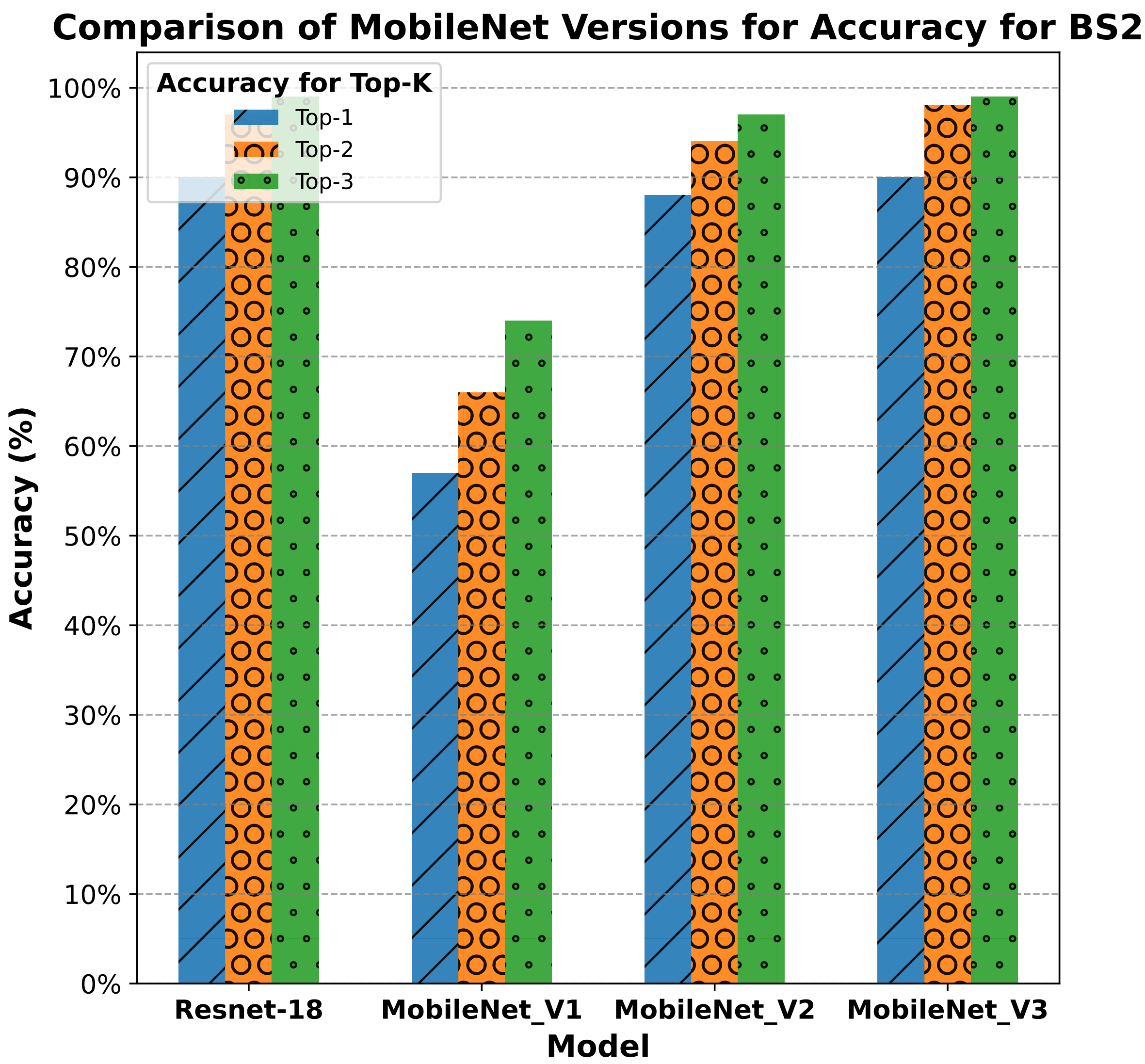

Figure 5.5: This figure depicts the top-k (k = 1, 2, 3) beam prediction accuracies of the proposed lightweight beam prediction model. The picture compares the top-k accuracies of various MobileNet models with the baseline ResNet-18 model for Base Station 1 (BS2).

Table 5.5: Performance Metrics for MobilenetV2 and Resnet-18 in Scenarios BS2

Scenario	**Precision**	**Recall**	**F1 Score**
MobilenetV2	0.881725	0.884050	0.876170
Resnet-18	0.864743	0.873699	0.864025

5.6.2 Confusion Matrix Analysis

In this study, we assess the performance of two deep learning models, MobileNetV2 and ResNet-18, for predicting optimal beam indices in scenario BS-1. The performance of these models is illustrated using confusion matrices, as shown in Figure 5.6 and 5.7.

- **Model Accuracy:** Both MobileNetV2 and ResNet-18 demonstrate strong predictive capabilities, as demonstrated by the prominent diagonal in their respective confusion matrices. This diagonal dominance shows that the models correctly predict the beam indices with high accuracy. A perfect prediction scenario would demonstrate as an entirely diagonal confusion matrix, where each predicted label matches the true label.

- **Mispredictions and Their Closeness:** While there are some off-diagonal elements indicating mispredictions, these instances are thin and, importantly, close to the diagonal. This indicates that even when the models do not predict the exact beam index, the predicted indices are still near the correct ones. Such closeness in mispredictions could be critical in applications where near-optimal beam selection is sufficient, thus ensuring that the overall system performance remains vigorous despite minor prediction errors.

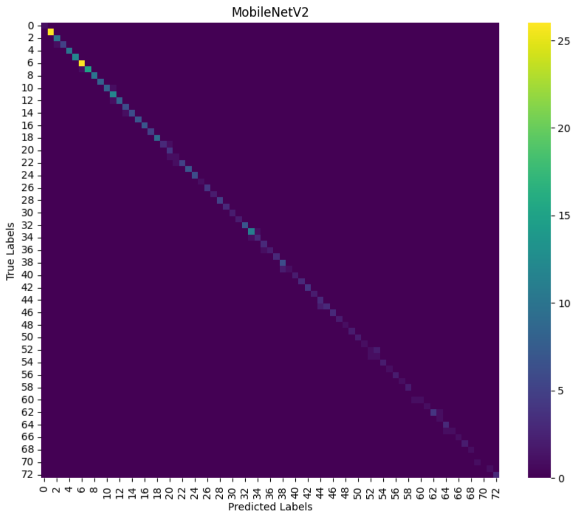

Figure 5.6: This figure illustrates the confusion matrices for the top-1 predicted beam indices with MobileNetV2 in Scenario BS-1

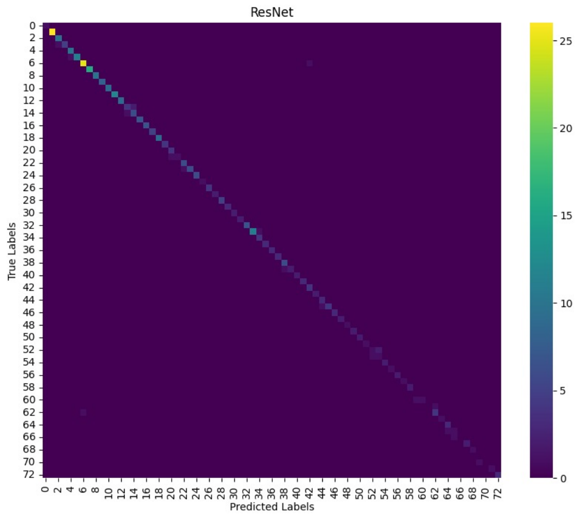

Figure 5.7: This figure illustrates the confusion matrices for the top-1 predicted beam indices with Resnet-18 in Scenario BS-1

5.6.3 Latency Analysis

The study investigates the latency differences between off-device and on-device inference. The graph presented in Figure 5.8 and 5.9 illustrates a comparison of overall latency for both methods, showcasing significant improvements when employing on-device inference. Latency components are derived from empirical measurements from equation 5.8:

where:

- T_{capture} is the time taken to capture an image, which is 38.5 milliseconds (ms),
- T_{transmit} is the time required to transmit the image for processing, which is negligible due to the direct on-device processing,
- $T_{\text{inference}} = 19.29\,\text{ms}$, based on MobileNet processing benchmarks for edge devices.

Applying these values, the overall inference latency is calculated as:

$$L_{\text{total}} = 38.5 \text{ ms} + 0 \text{ ms} + 19.29 \text{ ms} = 57.79 \text{ ms}$$

There is a significant decrease in overall latency as compared to the conventional inference method, which involves conducting inference off the UAV. Previously, when the inference was processed off-device, the system measured a delay of 68.52 ms. By implementing inference capabilities on-device, this delay is reduced to 59.5 ms. The figures in 5.8 and 5.9 demonstrates significant efficiency improvements for BS-1 and BS-2, respectively. It shows a latency reduction of 15.29% for on-device MobileNet inference and 6.45% for on-device ResNet-18 compared to off-device inference. This reduction is important for real-time applications such as beam prediction in UAV communication systems.

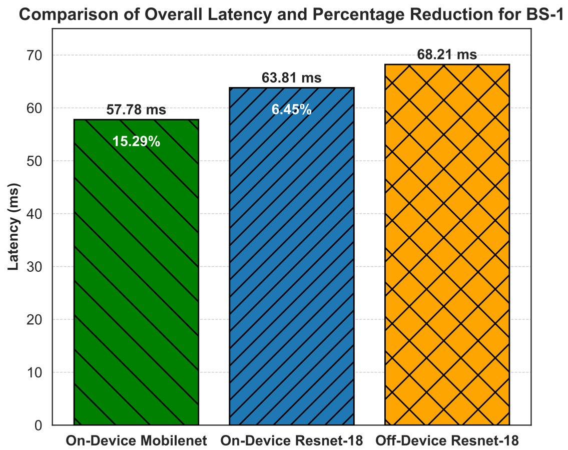

Figure 5.8: Comparison of inference latency for MobileNetV2 and ResNet18 during on-board and on-ground training in Scenario BS-1.

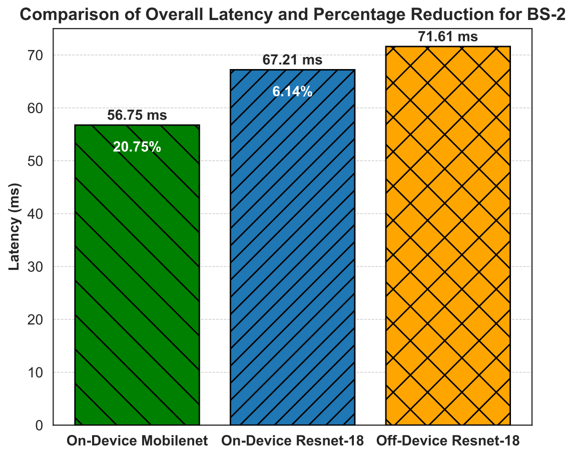

Figure 5.9: Comparison of inference latency for MobileNetV2 and ResNet18 during on-board and on-ground training in Scenario BS-2.

The reduction in latency not only enhances the responsiveness of the system but also improves the adaptability and reliability of the network in dynamic environments. By minimizing the time spent on image capture, transmission, and processing, the proposed framework ensures that the UAV communication systems can swiftly respond to changing conditions, an essential feature for mmWave communications which are susceptible to rapid changes in environmental dynamics.

5.6.4 Communication Cost Analysis

The comparative analysis of energy efficiency, based on the energy estimates given in equation (9). For on-device learning, equation (9) is adjusted as described in [177]:

$$E_{\text{est}} = [E(\kappa \times t_c) + 1 + (\delta \times D_{\text{trn}})] \tag{5.10}$$

where E represents the number of epochs during the training process. In centralized learning, E is set to 40, while κ and δ are maintained at 0.003 and 0.0001, respectively, for simplicity. The addition of 1 in the equation accounts for the model-sharing cost from the edge to the off-device server, such as a ground base station. For MobilenetV2 the computation time t_c per epoch is recorded as 304 seconds, and the data size D_{trn} is 147 KB. The calculation is given by:

$$E_{\text{est}} = 40(0.003 \times 304) + 1 + (0.0001 \times 147)$$

Therefore, the estimated energy E_{est} for centralized learning is approximately 37.4947 W and 40.3747 W for resnet-18 .

For off-device learning, equation (17) is modified to:

$$E_{\text{est}} = [E(\kappa \times t_c) + (\delta \times D_{\text{trn}})] \tag{5.11}$$

where E is the number of epochs. The calculation is given by:

$$E_{\text{est}} = 40(0.003 \times 328) + (0.0001 \times 360738)$$

Consequently, the energy estimates E_{est} for resnet-18 off-device learning is approximately 75.4338 W.

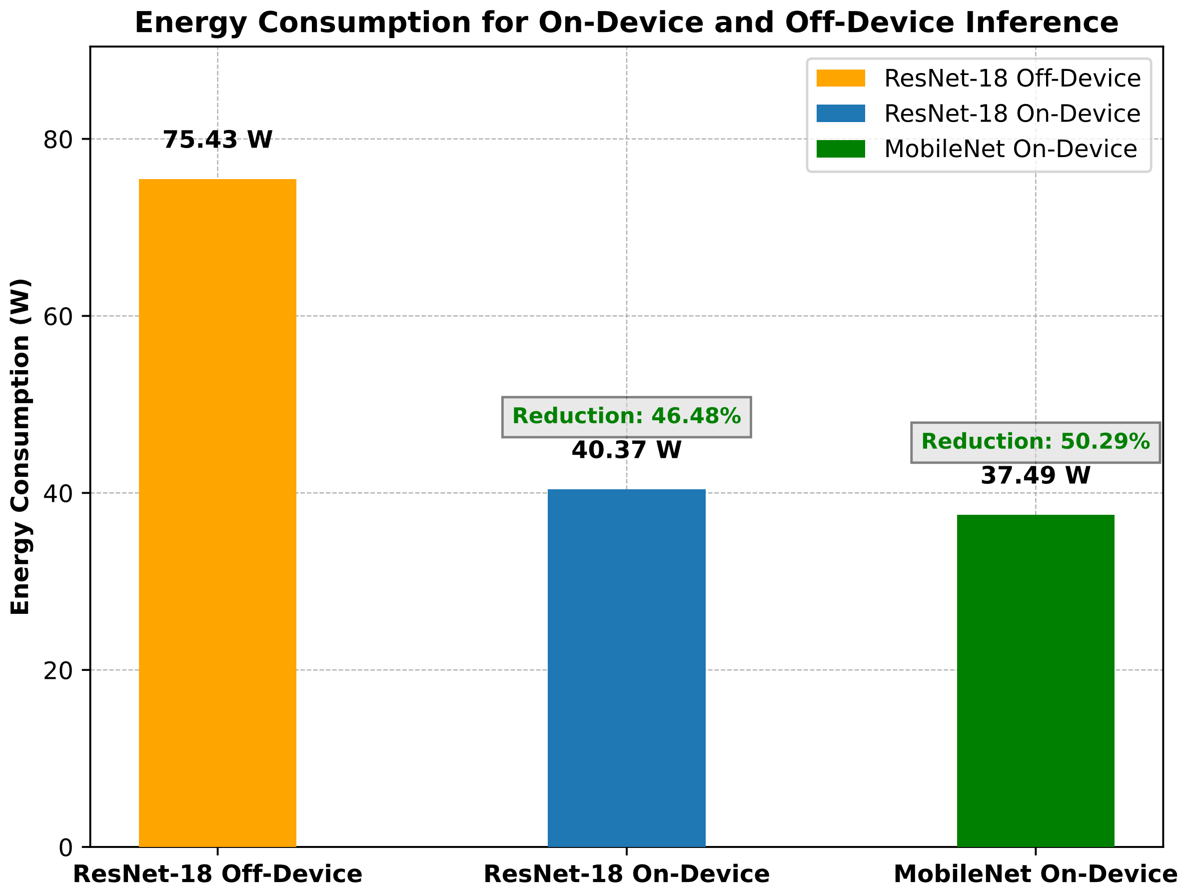

Figure 5.10: This figure shows the energy estimation for MobilenetV2 and resnet-18 on-device and off-device learning.

These results demonstrate a 50.29% reduction in energy consumption using on-device MobileNet inference compared to centralized ResNet-18 processing, making the proposed approach viable for energy-constrained UAV operations.

5.7 Chapter Summary

This chapter presents a cutting-edge approach to enhancing latency-aware vision-aided wireless communication in UAV-assisted networks. By integrating Mobilenet models (MobilenetV2 and MobilenetV3) with visual and communication data, the research achieves a significant improvement in beam prediction accuracy for UAVs. The results illustrate an impressive nearly 90% accuracy for top-1 beam predictions and near-perfect accuracy for top-3 and top-5 beams. A key innovation of this study is the use of onboard training directly on UAVs, which reduces latency by 15.29% compared to traditional ground-based training methods. This reduction marks a substantial improvement in real-time communication efficiency. The method's effectiveness is further validated through comparative analysis with the baseline Resnet-18 model using the ViWi_Drone dataset, demonstrating its potential to significantly enhance the performance of mmWave UAV communication networks.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

The research presented in this dissertation addresses critical challenges in the field of 5G and beyond wireless communication, particularly in the context of UAVs. Through the development of innovative vision-assisted and machine learning-based techniques, this work contributes to enhancing the reliability, accuracy, and efficiency of UAV communication networks.

Chapter 3 introduced a novel vision-assisted beam prediction model that significantly improves the accuracy of beam selection in UAV communication. The research explored the integration of multi-modal data fusion techniques to enhance beam prediction accuracy, a critical factor in maintaining reliable communication links between UAVs and ground stations. The proposed model, which leverages computer vision (YOLO-v5) and ensemble learning (stacking), demonstrated significant improvements in precision, recall, F1 score, and accuracy compared to traditional vision-based and position-based models. By employing a stacking methodology, the proposed model achieved an impressive 90% accuracy for top-1 beam predictions and nearly 100% accuracy for top-3 and top-5 beam predictions. This development is an essential step forward in providing UAVs with strong and reliable communication links for UAVs, particularly in dynamic and challenging environments.

In Chapter 4, the focus shifted to proactive blockage prediction for UAV-assisted handovers in future wireless networks. The integration of machine learning and computer vision has made it possible to develop a multi-modal handover framework capable of predicting and mitigating potential communication blockages before they occur. The proactive handover mechanism, validated through simulations, demonstrated a 20% improvement in overall network performance, highlighting its potential to maintain seamless connectivity and enhance the Quality of Experience (QoE) for users.

Chapter 5 further advanced the research by analyzing latency-aware vision-aided wireless communication in UAV-assisted networks. The study found that onboard training, where the model is trained directly on UAVs, reduced latency by 15.29% compared to conventional ground-based methods that involve sending data to a ground station for processing. This reduction in latency is crucial for real-time communication applications, ensuring that UAVs can operate efficiently even in time-sensitive scenarios.

Collectively, these chapters highlight the potential of integrating vision-based techniques with machine learning to address some of the most critical challenges in UAV communication. The proposed methods not only enhance the accuracy of communication predictions and the robustness of handover processes but also contribute to reducing latency and energy, which is critical for the future of real-time wireless networks.

6.2 Future Work

While the results presented in this dissertation are promising, there remain several areas for future research that could further enhance the capabilities of UAV-assisted communication systems in mmWave frequency bands:

6.2.1 Scalability and Real-Time Implementation

Future research should focus on scaling the proposed model for real-time implementation in large-scale UAV networks. This will involve optimizing the computational efficiency of the model and ensuring it can handle the high data throughput and processing demands required for real-time applications. Exploring hardware acceleration techniques, such as the use of GPUs or FPGAs, could be a valuable direction for this effort.

6.2.2 Generalization Across Diverse Environments

The current model was evaluated simulations and datasets like ViWi, which may limit its generalizability to other environments. Future work should explore the model's performance across diverse scenarios, including urban, rural, and disaster-stricken areas. This could involve collecting and incorporating additional datasets that capture a wider range of environmental conditions and UAV operating scenarios.

6.2.3 Integration with 6G Networks

As the world moves towards the adoption of 6G technology, there is a need to investigate how the proposed vision-assisted and machine learning models can be adapted and optimized for 6G networks. This includes exploring new frequency bands and communication protocols that will be introduced with 6G.

6.2.4 Cross-Disciplinary Applications

The techniques developed in this research have the potential to be applied beyond UAV communication, in areas such as autonomous vehicles, smart cities, and the IoT. Future work could explore these cross-disciplinary applications, leveraging the strengths of the proposed models in various contexts.

6.2.5 Real-World Testing and Validation

Future research should focus on evaluating the proposed energy and latency-efficient model in real-world settings. This includes using UAVs in real-world scenarios to actively detect blockages, monitor user mobility, and assess the overall impact on QoE). Researchers can improve the models' applicability for practical applications by comparing actual results to simulations.

6.2.6 Robustness Against Adverse Conditions

Finally, future work should address the robustness of the model against adverse conditions such as extreme weather, signal interference, and high-speed mobility. Developing strategies to mitigate the impact of these factors on beam prediction accuracy will be crucial for ensuring reliable communication in challenging environments.

In conclusion, while this dissertation has made significant contributions to the field of UAV-assisted communication, there remains substantial potential for further research and development. By continuing to refine and expand upon the models presented here, future researchers can contribute to the ongoing evolution of wireless communication technologies, ensuring that UAVs and other advanced systems can operate with the highest levels of efficiency and reliability.

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