AI-Enhanced VLC/RF Hybrid for Smart IoT: A Revolution

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***Abstract*—This paper presents a comprehensive survey of artificial intelligence (AI) techniques deployed in the context of hybrid systems, illuminating their utility and proposing distinct areas for AI application. The paper further highlights the most recent advancements in this rapidly evolving field. A rigorous performance analysis is conducted on a selection of ensemble learning, namely AdaBoost C4.5, Bagging, Gradient Boosting Machine (GBM), XGBoost, and LightGBM. These models are evaluated on a dataset with varying training sizes to assess their robustness and scalability. In addition to the evaluation, the paper explores the impact of hyperparameter optimization on the performance of these models. The results consistently demonstrate an enhancement in the classifiers' performance commensurate with an increase in training size. Specifically, GBM and AdaBoost C4.5 exhibit significant performance improvements with larger training sizes. In the absence of optimization, GBM achieves the highest accuracy at 96.62%. However, when hyperparameter optimization is employed, both GBM and XGBoost display substantial improvements, reaching an accuracy nearing 98.81%. The paper concludes with a discussion on future research directions related to the application of AI in hybrid systems. The findings from this study provide a robust foundation for further investigations and advancements in this promising and dynamic field.**

***Index Terms*—Visible Light Communication, Smart IoT, OpenVLC, AI.**

I. Introduction

In recent years, the rapid evolution of wireless communication technologies has spurred a significant interest in the exploration of innovative solutions to meet the escalating demand for high-speed, energy-efficient, and secure indoor communication systems. A promising approach that has emerged is the integration of Visible Light Communication (VLC) with traditional Radio Frequency (RF) systems, resulting in a hybrid VLC/RF system. A number of studies have delved into various methodologies for integrating VLC and RF networks, leading to the conception of hybrid systems specifically designed for indoor environments. Some researchers have emphasized on parallel structures where VLC and RF operate independently [1], [2], while others have examined more tightly integrated solutions, such as cooperative, or interworking structures [3], [4].

Artificial intelligence (AI) has emerged as a potential tool to enhance the performance and efficiency of hybrid VLC/RF systems. AI techniques can be applied to various aspects of these systems, including network planning and design, user experience optimization, resource management, fault detection and recovery, and predictive maintenance [5]–[7]. By intelligently analyzing data and making decisions, AI can significantly improve the performance, reliability, and user experience of hybrid VLC/RF systems. There are variety of AI application can be applied in hybrid system and we will discuss it further in Section II.

In previous work, we are proposed an intelligent management system (IMS) platform which is crucial part in hybrid system. IMS act like a brain of the system and take care a different aspects in system from system operation to resource optimization [8]. The IMS plays a crucial role in controlling operations in hybrid networks, particularly during handover procedures. By deploying algorithms using fuzzy logic and machine learning, the IMS can adapt to different scenarios, thereby improving robustness and ensuring seamless user experiences.

This paper makes the following contributions:

- We offer a comprehensive review of state-of-the-art machine learning applications in hybrid systems, incorporating the latest research. We address the challenges and propose potential solutions that could shape the future of this field.
- We introduce a robust AI model that acts as the central controller of the system, specifically managing handover operations in our hybrid VLC/WiFi networks. The findings of this study could be applied to other contexts as well. Additionally, we discuss future directions for AI in hybrid networks.

In this paper, we provide a comprehensive literature review on the AI in hyrbid VLC/RF networks, which is presented in Section II. Following this, we introduce the various machine learning methodologies that will be utilized in our experiments in Section III. Section IV details the setup scenarios for the hybrid system that we have established. Our promising results, particularly relating to the development of a robust handover mechanism for IMS, are showcased in Section V. Subsequently, in Section VI, we discuss and present various directions for future research. Finally, our conclusions are drawn in Section VII.

II. Literature Review about AI in Hybrid Systems

The emergence of hybrid networks, a combination of different network types to optimize performance, has generated considerable interest in the application of AI. The potential of AI to improve network planning and design, enhance user experience, manage resources effectively, facilitate fault detection and recovery, and enable predictive maintenance is increasingly evident, as illustrated in Figure 1.

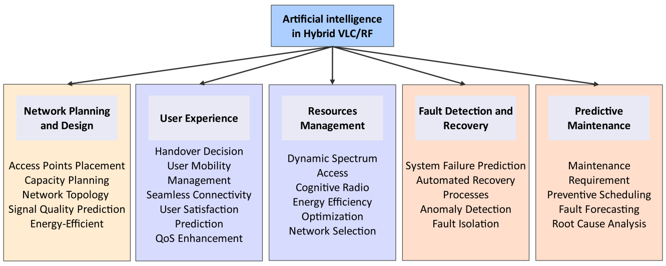

Fig. 1. Overview of AI implementation in Hybrid VLC/RF Systems.

a) Network Planning and Design: The planning and design of hybrid networks have been significantly influenced by AI. It optimizes access point placement to maximize coverage and minimize interference [9], and aids capacity planning by predicting network traffic and user behavior. AI also enhances network topology design, improving performance and resilience. AI's predictive capabilities also enable effective management of network parameters based on factors like distance, obstacles, and interference. Moreover, modulation schemes can be optimized based on network conditions, augmenting data rate and signal quality [10]. AI can also improve localization accuracy by fusing data from various sources and applying advanced estimation techniques. Finally, network design can be optimized to minimize energy consumption, contributing to environmental sustainability.

b) User Experience: The user experience in hybrid networks can be substantially enhanced by leveraging AI. Machine learning algorithms optimize handover decision-making processes by predicting user mobility and network conditions to proactively make handover decisions, reducing call drop rates and ensuring service continuity [8]. Predictive algorithms also adjust network parameters dynamically based on user movement patterns, ensuring optimal connectivity and service quality [11]. These algorithms can also predict the optimal network for connection, considering factors like signal strength, network congestion, and user preferences. Predictive models also forecast user satisfaction, aiding network operators in tailoring their services. AI enhances Quality of Service (QoS) by optimizing network parameters, considering factors like latency, throughput, and packet loss rate. AI's ability to predict traffic patterns enables effective network resource management. Moreover, analyzing user behavior and preferences using AI can lead to personalized services, thereby enhancing user satisfaction and loyalty.

c) Resources Management: Resource management in hybrid networks is significantly enhanced by the application of AI. Dynamic spectrum access in hybrid networks can be optimized, enhancing spectrum utilization and reducing interference. AI also improves the performance of cognitive radio networks by optimizing parameters such as spectrum sensing, spectrum decision, and spectrum sharing. Optimization of network selection based on factors such as signal strength, network conditions, and user preferences improves network performance and user experience. Load balancing is another area where AI can contribute by efficiently distributing network traffic to optimize resource utilization and ensure service continuity [7], [12]. Resource allocation can be optimized based on network conditions and user demands, enhancing network performance and QoS. Interference in hybrid networks can be managed by predicting and mitigating potential interference sources, enhancing signal quality and network performance. Lastly, effective management of network traffic is ensured by predicting traffic patterns and adjusting network parameters accordingly, ensuring optimal performance and QoS.

d) Fault Detection and Recovery: The application of AI in detecting and recovering from faults in hybrid networks is substantial. It enables proactive maintenance and downtime reduction by predicting system failures based on historical data and network conditions. AI can automate recovery processes, reducing recovery time and minimizing the impact of failures. It also facilitates early detection of potential issues by detecting anomalies in network traffic and system behavior [13]. AI enhances network security by detecting intrusions based on network traffic patterns and aids in isolating faults for targeted troubleshooting, thus reducing recovery time.

e) Predictive Maintenance: Predictive maintenance in hybrid networks benefits significantly from AI. It enables proactive maintenance and downtime reduction by predicting system maintenance requirements. AI can optimize preventive maintenance scheduling based on these predictions, enhancing system reliability and lifespan. AI aids in early detection and mitigation of potential issues by forecasting faults [14]. It can predict the life expectancy of network equipment based on usage patterns and condition monitoring data, enabling proactive replacement and reducing downtime. AI can monitor the health of network equipment by analyzing condition data and detecting anomalies. It also allows root cause analysis of network issues by identifying patterns in network data for targeted troubleshooting and recovery. Lastly, AI can manage spare parts effectively by predicting requirements based on maintenance data and network conditions, reducing downtime and maintenance costs.

f) Literature Review: The literature review showcases the versatility of AI in optimizing various aspects of hybrid VLC/RF systems in Table I. Notably, AI plays a pivotal role in network planning and design, with methods such as Regression (REG) and deep neural networks (DNN) being used to enhance network performance and accurately estimate user positions and orientations. This leads to more efficient and reliable system operation.

Furthermore, AI techniques have significantly improved the user experience in hybrid networks. The use of artificial neural networks (ANN) and reinforcement learning (RL) allows for dynamic adjustment of network preferences based on user behavior and network conditions. These methods also enable the prediction of user movements and proactive management of network handovers and blockages, leading to smoother and more reliable connectivity. In the realm of resource management, deep learning proves instrumental in enhancing load balancing in hybrid networks. By intelligently allocating resources, these methods improve network throughput and reduce runtime, leading to more efficient network operation and better user experience. Overall, the application of AI in hybrid LiFi/WiFi systems presents promising potentials for future advancements in the field.

Despite the promising advancements in AI for hybrid VLC/RF systems, the literature reveals some notable shortcomings. A significant limitation is that most of the existing studies are based on simulations, with a lack of actual testbed implementations. While simulations are crucial for initial testing and development, they often fail to capture the com-

TABLE I
AI IN HYBRID SYSTEM

Categories	Ref.	Methods	Remark
Network Planning and Design	[10]	REG	New hybrid OFDM method for LiFi, which is power-efficient and offers a wide dimming range. It uses a novel switching algorithm and machine learning to optimize the system's performance.
	[15]	DNN	Estimate user 3D position and equipment orientation in indoor LiFi systems.
User Experience	[11]	ANN	Dynamically adjusts the selection preference between LiFi and WiFi, considering channel quality, resource availability, and user mobility.
	[5]	RL, CL	A novel machine learning-based handover scheme enhances network throughput in hybrid LiFi/WiFi environments by predicting user trajectories and making adaptive handover decisions.
	[6]	ANN	An algorithm that uses machine learning to predict VLC blockage intervals and proactively switch between LiFi and WiFi, ensuring high data rates and minimal disruption.
Resources Management	[12]	DNN	An user-centric load balancing framework for hybrid LiFi and WiFi networks, which significantly improves network throughput and reduces runtime compared to traditional methods.
	[7]	DNN	Adaptive structure for load balancing can accommodate varying numbers of users without retraining, providing near-optimal network and reducing runtime.
Fault Detection and Recovery	[13]	DNN	Secret key generation in 5G and beyond LiFi networks. The model mitigates concept drifts due to user density changes, maintaining stable key generation rates.
Predictive Maintenance	[14]	DNN	Developed to forecast future user positions, orientations, and associated channel coefficients, providing a solution to mitigate the LiFi channel aging issue.

plexities and unpredictable nature of real-world environments. This gap between simulation and actual implementation can lead to overestimations of the performance of the proposed methods. Furthermore, many studies do not account for the computational time of their proposed methods. This is a critical aspect, especially in the context of user experience, as the efficiency of a method is not solely determined by its performance but also by how quickly it can deliver results. Computational time becomes even more crucial in real-time applications, where delays can significantly degrade the user experience.

In contrast to the existing literature, our approach has testbed implementation. This dual approach allows us to verify the performance of our proposed methods in a controlled environment and then validate their effectiveness in a real-world setting. Moreover, our methodology takes into account the computational time of the proposed methods, especially in relation to user experience during handover procedures [8]. By doing so, we aim to provide a comprehensive and realistic evaluation of our methods, contributing to the advancement of AI applications in hybrid VLC/RF systems.

III. Methodology

Machine learning has become a cornerstone of modern technology and is increasingly being applied to enhance the performance of hybrid VLC and RF systems. This section explores the application of various machine learning techniques, specifically ensemble learning, for optimizing the performance of these hybrid systems. Our aim is to improve the results of our previous experiments by employing ensemble learning and hyperparameter optimization techniques.

A. Ensemble Learning

Ensemble learning is a powerful machine learning paradigm that combines multiple learning algorithms to achieve better predictive performance than could be obtained from any of the constituent learning algorithms alone. It is a promising approach to enhance the accuracy of predictions, avoid overfitting, and improve the robustness of models, making it highly suitable for enhancing the performance of hybrid VLC/RF systems.

1) Bagging Classification: Bagging, or Bootstrap Aggregating, is a method that involves manipulating the training set by resampling and running algorithms on it. Each model makes its predictions independently, and the final prediction is determined by averaging the predictions from all models. In the context of our hybrid VLC/RF system, bagging could be utilized to improve the robustness and stability of handover decisions. By incorporating bagging classification, we can build a system that is resilient to fluctuations and can maintain high performance even in uncertain conditions.

2) Adaptive Boosting (AdaBoost): AdaBoost is a boosting algorithm that combines weak learners into a weighted sum that represents the final output of the boosted classifier. It is adaptive in the sense that subsequent weak learners are tweaked in favor of those instances misclassified by previous classifiers. This iterative process of learning from mistakes makes AdaBoost a powerful tool for enhancing the accuracy of handover decisions in our hybrid VLC/RF system. Our previous work has demonstrated the efficacy of AdaBoost, where the AdaBoost C4.5 algorithm achieved a remarkable 97.5% accuracy rate in predicting handover decisions.

3) Gradient Boosting: Gradient Boosting is an ensemble learning algorithm that constructs a predictive model from an ensemble of weak models, typically decision trees. It builds models stage-wise and allows optimization of an arbitrary differentiable loss function. Variations of gradient boosting, such as GBM, XGBoost, and LightGBM, have demonstrated potential across various applications.

GBM, utilizing decision trees as weak learners, leverages gradient descent optimization to optimize a differentiable loss function. Its iterative learning process makes it suitable for optimizing handover decisions in our hybrid VLC/RF system, enabling efficient and reliable decisions.

XGBoost, an advanced Gradient Boosting implementation, offers accurate approximations using hardware optimization and parallel computing, enhancing speed and efficiency. Its ability to quickly train models without sacrificing accuracy makes it essential for real-world hybrid VLC/RF systems requiring swift and accurate decisions.

LightGBM, a gradient boosting framework utilizing tree-based algorithms, is designed for efficiency and speed. Its potential for real-time handover decisions in hybrid VLC/RF systems makes it a prime candidate, facilitating quick, accurate decision-making.

B. *Hyperparameter Optimization Techniques*

Hyperparameter optimization is a vital step in machine learning, responsible for identifying the optimal hyperparameters for a learning algorithm, thereby enhancing model performance. This section briefly discusses three prevalent techniques: Grid Search, Random Search, and Bayesian Optimization, and their potential utility in hybrid VLC/RF systems.

1) Grid Search: Grid Search, a traditional hyperparameter tuning method, entails an exhaustive search through a pre-specified hyperparameter subset. Each parameter combination is used to train the model, and its performance is evaluated using cross-validation. Despite being computationally demanding, Grid Search can be beneficial in hybrid VLC/RF systems where the optimal configuration is unknown.

2) Random Search: Random Search employs random hyperparameter combinations to optimize the model. Each combination is used to train the model and calculate the validation score. The process repeats for a set number of iterations, and the best performing hyperparameters are selected. Given its efficiency in higher-dimensional spaces, Random Search is a suitable candidate for hyperparameter tuning in hybrid VLC/RF systems.

3) Bayesian Optimization: Bayesian Optimization is an advanced hyperparameter tuning approach that uses a Gaussian Process to model the objective function. Each step involves fitting the Gaussian Process to the known samples and maximizing the acquisition function to select the next sample. This technique is particularly useful in computationally expensive scenarios, aiming to find the best hyperparameters with minimal evaluations, making it ideal for tuning hyperparameters in hybrid VLC/RF systems.

IV. Experimentation

Our experimental setup comprises a testbed designed to simulate a real-world hybrid environment. This testbed includes OpenVLC transmitters and OpenVLC receiver that have been integrated with WiFi capabilities, as shown in Figure 2. More information about this setup can be find in our previous paper **??**. This integration enables efficient data transmission over both visible light and WiFi channels, thus providing a robust platform for our experiments. The network infrastructure is managed by an IMS, which serves as the central controller. This setup is further complemented by a stream clients and a stream server, simulating a realistic network traffic scenario. To add another layer of complexity and to mimic real-world network fluctuations, we have incorporated a WiFi Jammer. This device is designed to create interference in the WiFi channel, thereby generating different channel conditions that test the robustness of our handover decision-making process.

The mobility within the network is represented by two OpenVLC units, each equipped with customized firmware. These units are mounted on a mobile stand that can move freely between the two access points, thereby simulating the movement of a user within the network. This mobility aspect is crucial for testing the handover mechanism between VLC and WiFi networks. As part of our comprehensive experimental study, we have conducted multiple tests in a variety of indoor environments. These tests were designed to rigorously evaluate the effectiveness of our proposed hybrid handover solution under different conditions. During each test, the receiver VLC units were move in a consistent cycle for a duration of five minutes. These movements allowed us to collect a substantial amount of data related to the system's ability to handle handovers seamlessly between VLC and WiFi networks.

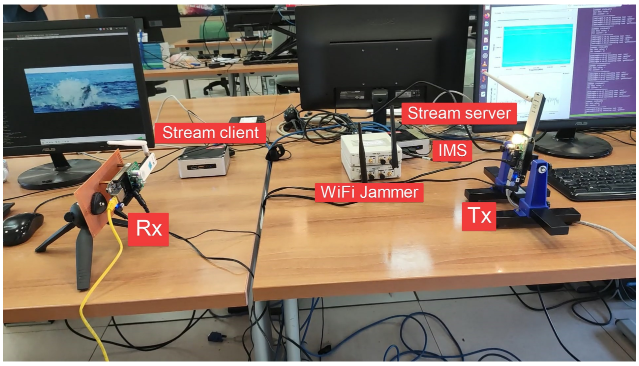

Fig. 2. Testbed for VHO with actual streaming video application.

The dataset collected for this study encompasses a variety of metrics, including *Maximum RSSI*, *Minimum RSSI*, the standard deviation of RSSI (*sRSSI*), the *current network*, *WiFi data rate*, *WiFi link quality*, and *WiFi noise level*. The values of these metrics, obtained during the testing phase, are invaluable. They serve as the training set for the machine learning models discussed in the previous sections. These models are subsequently employed to make intelligent and efficient handover decisions in our hybrid VLC/RF system. For researchers interested in replicating our testbed or seeking more detailed information about the setup, a link is provided [16]. This link grants access to comprehensive details about our testbed's configuration, thereby facilitating easier replication under various circumstances.

V. Results and Discussion

The performance of various ensemble learning classifiers, as presented in Table II, demonstrates an intriguing relationship between the choice of classifier, the size of the training set, and the utilization of hyperparameter optimization techniques. The classifiers considered in this analysis include AdaBoost C4.5, Bagging, GBM, XGBoost, and LightGBM.

All classifiers exhibit a trend of improved performance with an increase in training size, which aligns with the general expectation in machine learning models. However, the magnitude of this improvement varies across classifiers. Bagging and AdaBoost C4.5 demonstrate the most significant improvement relative to their own performance at lower training sizes. Without optimization, GBM yields the highest accuracy of 96.62% with an 80% training size. However, with hyperparameter optimization, GBM and XGBoost exhibit a notable improvement, with GBM reaching an accuracy of 98.80% and XGBoost reaching 98.81% at the same training size show in Figure 3. This suggests that GBM and XGBoost

TABLE II
PERFORMANCE OF ENSEMBLE LEARNING

Classifier	**Training Size** (%)	**Accuracy** (%)	**Accuracy with opts** (%)
AdaBoost C4.5	40	86.83	88.49
	60	91.41	93.41
	80	95.48	97.48
Bagging	40	87.62	88.81
	60	93.41	93.51
	80	96.34	98.03
GBM	40	86.62	87.63
	60	91.41	92.41
	80	96.62	98.80
XGBoost	40	85.83	86.83
	60	91.41	92.41
	80	96.34	98.81
LightGBM	40	86.62	87.62
	60	91.82	92.81
	80	96.02	97.86

could potentially outperform other classifiers when their hyperparameters are optimally tuned.

The effect of hyperparameter optimization is not uniform across all classifiers. For AdaBoost C4.5 and Bagging, optimization leads to a consistent slight improvement in accuracy across all training sizes. In contrast, for GBM and XGBoost, the benefit of optimization is less consistent, indicating that the hyperparameter search space or the optimization method may need to be adjusted for these classifiers. Based on these results, both XGBoost and GBM with hyperparameter optimization emerge as strong contenders, achieving an accuracy of 98.81% and 98.80% respectively with an 80% training size. This suggests that the choice of classifier could depend on other factors such as computational cost, model interpretability, and application-specific requirements.

While hyperparameter optimization can enhance model performance, it is crucial to weigh this improvement against the associated computational costs. In the context of IoT applications, considerations extend beyond computational resources to include factors such as power consumption and real-time processing capabilities. In our analysis, optimization yielded an increase a few percentage points, but necessitated substantial computational resources. Moreover, the power and time requirements for optimization, particularly with ensemble methods, may be prohibitive in many IoT scenarios. Given the relatively modest improvement and these significant demands, it may be more cost-effective to employ non-optimized models when they already yield high accuracy. The decision to use optimized models should be informed by a comprehensive assessment of factors, including the specific requirements of the IoT application, available resources, real-time processing needs, power constraints, and the importance of maximizing accuracy.

Table III presents the feature scores for XGBoost with best optimization. According to the table, *sRSSI* emerges as the most influential feature in the optimized XGBoost model, boasting the highest score of 0.32. It is closely followed by *Minimum RSSI* and *Maximum RSSI*, with respective scores

TABLE III
FEATURE SCORES BASED ON XGBOOST WITH OPTIMIZATION

Feature	**Score**	**Rank**
sRSSI	0.32	1
Minimum RSSI	0.21	2
Maximum RSSI	0.10	3
Current network	0.15	4
WiFi data rate	0.12	5
WiFi link quality	0.05	6
WiFi noise level	0.05	6

of 0.21 and 0.10. Features such as *Current network* and *WiFi data rate* also contribute to the model's predictions, albeit to a lesser extent. Conversely, *WiFi link quality* and *WiFi noise level* exert the least influence on the model, both scoring a mere 0.05. These findings offer valuable insights for future feature selection and engineering efforts. However, it's crucial to remember that feature importance may vary depending on the specific model and dataset used.

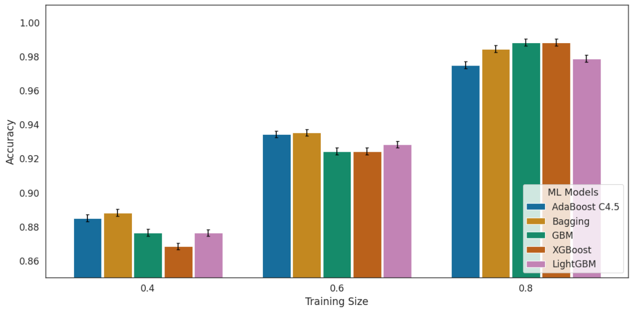

Fig. 3. Accuracy of Models with Hyperparameter Optimization.

VI. DISCUSSION AND FUTURE RESEARCH DIRECTIONS

We explore key aspects of hybrid VLC/RF networks, including access point placement, handover skipping, and the potential application of transfer learning. Each of these elements plays a crucial role in the performance and efficiency of networks, and offers promising avenues for future research.

a) Access Point Placement: Access point placement is a vital factor in the design and operation of VLC networks. The positioning of access points, also referred to as light sources, directly impacts the network's coverage and performance. Key factors to consider include the need for the light sources to provide sufficient coverage to target areas, which requires careful evaluation of the environment's light transmission properties, including potential obstacles and reflections.

Moreover, to ensure high-quality signal reception, the light sources must be strategically placed to avoid obstruction by other objects. This aspect becomes particularly critical in multi-floor buildings where numerous obstacles could hinder communication between light sources and receivers.

Furthermore, the power requirements of light sources must be considered. While high-power light sources can extend the network's coverage, they can also cause interference with other optical devices and increase the network's cost. Conversely, low-power light sources can minimize cost but may compromise the coverage area and signal quality. Optimizing the placement of access points can lead to a high-performing, cost-effective VLC network, a crucial development aspect in IMS.

b) Handover Skipping: Handover skipping is a technique that can significantly improve the performance and efficiency of VLC networks. In VLC networks, handover events can introduce considerable overhead. Handover skipping aims to reduce this overhead by minimizing the number of these events. This is achieved through advanced signal processing algorithms capable of accurately predicting a device's future position and determining the most optimal access point for the device to connect to.

These algorithms consider various factors such as the device's movement speed, the signal strength and quality of each access point, and the availability of resources on each access point. By minimizing the number of handover events, handover skipping ensures that the device is always connected to the most optimal access point, leading to a more efficient and stable VLC network. This technique also has the potential to reduce power consumption and increase the battery life of devices, as less time is spent searching for and connecting to new access points.

c) Transfer Learning: Transfer learning, a machine learning technique that repurposes a model trained on one task for another related task, presents a promising avenue for future research in IMS for hybrid VLC/WiFi systems. It can address challenges such as data scarcity and variations in channel characteristics in VLC systems by leveraging pre-existing models trained on large datasets. This improves accuracy and performance by adapting models to the specific characteristics of each system.

An interesting prospect for future research is applying transfer learning to repurpose models developed for handover scenarios in hybrid VLC/WiFi systems. Initially trained models for predicting device movement or optimizing signal strength can be reused and fine-tuned for tasks like predicting network traffic patterns, optimizing resource allocation, managing interference, or balancing network loads. This approach not only enhances the utility of the developed models but could also lead to more integrated and efficient hybrid VLC/WiFi systems. Thus, exploring such applications of transfer learning in hybrid systems is a promising direction for future research.

VII. Conclusions

This paper has provided an extensive review of the state-of-the-art AI applications in hybrid VLC/WiFi systems, focusing on the latest research in the field. We have highlighted the challenges that these systems face, such as access point placement, handover skipping, and transfer learning. We proposed potential solutions and future research directions that could significantly shape the future of this field.

A key contribution of our work is the reintroduction of an IMS platform that uses a robust AI model as the core controller of the hybrid VLC/WiFi networks. This model is specifically designed to manage handover operations, ensuring seamless communication and efficient resource use. Our study's results demonstrate the efficacy of this AI model, with XGBoost optimization notably achieving an accuracy of 98.81%. Other machine learning techniques also yielded competitive results, suggesting that our approach could be applied to other contexts within the hybrid system.

The findings of this study have implications beyond handover management. The machine learning model we developed could be repurposed for other tasks within the hybrid system, such as predicting network traffic patterns, optimizing resource allocation, managing interference, or balancing network loads. This potential repurposing of our model underscores the versatility of machine learning and its capacity to enhance network performance in various ways.

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