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An Analysis of Machine Learning Applications in Visible Light Communication Systems

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Abstract : With the growing use of high-bandwidth applications, visible light communication (VLC) has surfaced as a promising method for high-speed data transmission due to its dual capability of providing illumination and data transfer. However, VLC faces significant challenges due to various nonlinear distortions that affect signal processing and reduce system efficiency. Machine learning (ML) techniques offer a valuable approach to mitigating these negative effects of transceiver nonlinearity. ML can be applied to numerous VLC issues, such as channel estimation, jitter compensation, position tracking, modulation detection, phase estimation, and security. This study presents an in-depth review of various ML algorithms aimed at simplifying the design of indoor VLC systems and enhancing their performance. Additionally, it explores different ML applications, associated challenges, and potential future research directions in the context of VLC.

Keywords : *Visible Light Communication, Machine Learning, Wireless Communication.*

1. Introduction

In response to the growing need for high data rate transmissions, visible light communication (VLC) has become an increasingly popular area of research. VLC operates in the upper portion of the electromagnetic spectrum, which is free from licensing requirements and experiences minimal interference, while offering high data rates and spectrum efficiency [1, 2]. It is a cost-effective and energy-efficient technology, utilizing a spectrum that is 1000 times more efficient than radio frequencies and can concurrently provide both communication and illumination [3]. These benefits make VLC a promising alternative to traditional indoor radio frequency communications. Additionally, VLC is drawing interest for underwater communication applications, which require high-speed and long-distance wireless connectivity [4].

As technology progresses, managing large volumes of data presents more challenges, imposing constraints on communication networks in terms of bandwidth, latency, and reliability. To address these limitations, communication technologies and architectures have advanced, incorporating improved modulation techniques, innovative multiplexing methods, and enhanced security features. However, these advancements also add complexity, making systems more difficult to operate and manage [5]. Currently, optical communication systems are static, with a fixed physical channel path between source and destination, which simplifies hardware requirements. Future optical communication systems are anticipated to be dynamic, flexible with spectrum and modulation formats, programmable, and adaptable, which will enhance system performance, flexibility, and efficiency [5].

Machine learning (ML) approaches offer promising solutions for enhancing the intelligence of communication nodes. ML is well-suited for addressing complex problems that traditional methods struggle with or cannot solve. By replacing conventional software with ML techniques, systems can learn from previous data to tackle intricate issues [6]. In wireless communication, ML has advanced to the point where it can enable systems to understand and process information through data interactions. Researchers and engineers globally are exploring how ML protocols can aid in developing 5G standards [7, 8]. Despite the potential synergy between wireless communication and ML, they have often been studied separately. In channel modeling for wireless communication, algorithms based on probability and signal processing can sometimes show inaccuracies, leading to performance assessment errors. ML techniques can detect system flaws without the need for complex algorithms. Additionally, wireless signals, particularly optical data, often involve limited datasets [9]. ML can be applied to tasks such as channel estimation and forecasting [10–13], location tracking [14–17], and modulation identification [18–20] in wireless communication.

In VLC, various ML algorithms have been used to enhance system performance in different design scenarios. These algorithms help mitigate issues such as nonlinearities, noise parametrization, and complex input-output mapping [4, 21].

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Techniques like neural networks (NN), k-means clustering, and support vector machines (SVM) address channel deficiencies, optimize optical efficiency, and manage modulation and bit rate [22]. Indoor positioning within VLC networks has been explored using methods such as k-Nearest Neighbors (k-NN), weighted k-NN (wk-NN), artificial neural networks (ANN), and clustering [14–24]. Additionally, SVM, Gaussian mixture models (GMM), and k-means algorithms effectively handle the nonlinear degradation in VLC systems caused by phase variations [25, 26].

ML algorithms offer an effective means of tackling inherent limitations in high-speed VLC systems, such as nonlinearity, jitter, and security vulnerabilities. They can also be used to estimate modulation, phase, and channel characteristics, and to track user locations in real time. While some literature covers various ML algorithms for optical wireless communication (OWC) systems, such as modulation format identification (MFI) and optical performance monitoring (OPM) [5], and comparisons of ML algorithms for OWC systems [27], a comprehensive review specifically addressing ML techniques in VLC systems and their limitations is still lacking. This paper aims to fill this gap by providing a thorough review of ML algorithms that simplify VLC system design and enhance performance in various applications. The contributions of this study include:

1. A detailed review of different ML algorithms implemented in VLC networks.

2. Discussion of challenges in VLC system design, such as nonlinearity, jitter, and security, and the ML algorithms that can address these challenges.

3. Examination of ML applications in VLC-based indoor positioning and recent ML algorithms for channel estimation, phase estimation, and modulation identification to improve VLC transmission characteristics.

4. Analysis of future challenges and research directions for ML algorithms in VLC systems.

The paper is structured as follows: Section 2 describes an ML-based VLC system. Section 3 reviews ML algorithms applied to VLC systems. Section 4 discusses VLC limitations like transmitter-side nonlinearity, eavesdropping, channel distortion, jitter, and the impact of receiving nonlinearity on modulation and phase estimation, along with ML solutions. Section 5 compares different ML algorithms. Section 6 explores future challenges and potential applications of ML in VLC, with a concluding summary in Section 7.

2. ML-Based VLC System

In an indoor setting, visible light communication (VLC) systems utilize light-emitting diodes (LEDs) for both illumination and data transmission. The LEDs' intensity is modulated to achieve data rates up to gigabits per second (Gbps) [29]. Unlike radio frequency systems, VLC requires adjustments to modulation techniques to handle the intensity modulation constraints of LEDs and to meet the desired illumination levels [9].

A typical VLC system, as shown in Figure 1, consists of three main components: an LED-based transmitter, an optical VLC channel, and an optical photo detector (PD) receiver. The transmitter modulates a radio frequency carrier signal, pre-equalizes and up-converts it, and then modulates the LED light's intensity using an electrical signal. VLC can operate over free space (usually indoors) or underwater. The receiver performs various functions such as down-conversion, post-equalization, demodulation, and decryption to recover the original binary data. The bit error rate (BER) of this data, as determined from the decoded output, reflects the VLC system's performance [4]. Both the transmitter and receiver often incorporate machine learning (ML) techniques to enhance system performance. Key ML-based improvements include reducing nonlinearity, channel estimation, jitter compensation, location tracking, modulation detection, phase estimation, and ensuring security.

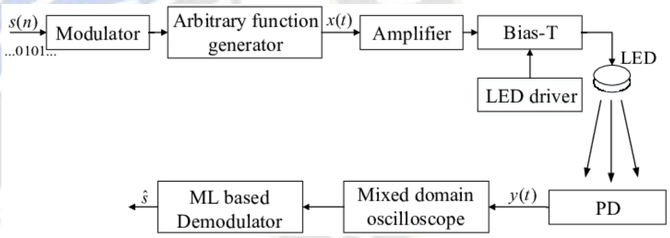

Figure 1: ML-based VLC System

3. Machine Learning

The goal of machine learning (ML) is to create algorithms that can establish relationships between input (i/p) and output (o/p) parameters using a sufficient amount of training data, without explicitly defining the nature of these relationships. This section discusses some commonly used ML algorithms in VLC networks.

3.1. Supervised ML

Supervised machine learning (SL) involves predicting an unknown function that maps inputs to outputs based on past data. During training, both input and output datasets are used, with the model learning the relationship between them. The model is iteratively improved by comparing predicted outputs to actual ones. Once trained, the model is tested with new input data to assess its accuracy, as illustrated in Figure 2.

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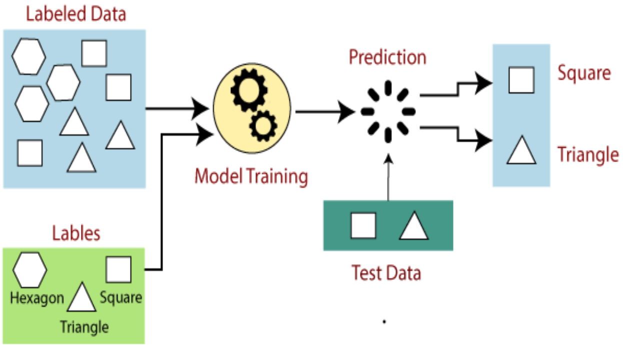

Figure 2: Supervised ML

Key supervised ML algorithms relevant to VLC systems include:

3.1.1. k-Nearest Neighbor (k-NN)

k-NN is a straightforward supervised learning method that relies on nonparametric techniques. It predicts outputs based on the relationships established during training between input and output datasets. Distances such as Manhattan, Hamming, and Euclidean are used to measure the proximity between data points.

During the training phase, the data is categorized and labeled to ease the search process. To estimate the output from input sets, the k-nearest neighbors method is utilized, which involves selecting the most frequent class among the k-nearest neighbors. For instance, Figure 3 illustrates data classification using the k-NN technique, with datasets assigned to one of three color-coded groups: blue, green, or yellow. Data that cannot be classified is marked in red. With k = 6, if three of the six nearest neighbors are green, two are blue, and one is yellow, the unidentified data would be classified as green.

In regression tasks, k-NN estimates the output by averaging the values of the k-nearest neighbors. The key approach to determining the best k value is to evaluate various k values and select the one that minimizes error. Although k-NN is effective for large datasets and nonlinear problems, its practical use is limited by storage requirements and latency issues [5].

3.1.2 Support Vector Machine (SVM): The goal of SVM is to find the most suitable hyperplane that divides the data into different categories. SVM can be either linear or nonlinear. In linear SVM, data points are separated by a straight line, while nonlinear SVM allows for separation using more complex, nonlinear boundaries [22]. Figure 4 shows a linear SVM. SVM involves two main components: the hyperplane and the support vectors. The optimal hyperplane is the one that is farthest from the data points, and the support vectors are the closest points to this hyperplane, significantly influencing its position.

3.1.3 Artificial Neural Networks (ANNs): ANNs are inspired by the human brain and mimic its structure. They consist of interconnected nodes, similar to neurons in the brain. ANNs are organized into multiple layers of nodes, as shown in Figure 5, which illustrates a structure with three layers.

The three layers of an Artificial Neural Network (ANN) include the input layer, hidden layer, and output layer. Data first passes through an activation function in the input layer before moving to the hidden layer, where it identifies patterns between inputs and features. The data then progresses through several transitions in the hidden layer to reach the output layer. In an ANN, the input's weighted sum, which includes a bias term, is calculated. Weights are parameters that influence the interaction between neurons, and their sum is sent to an activation function to determine whether a node activates. The output is derived from the activated nodes. A Deep Neural Network (DNN) is an ANN with two or more hidden layers, making it well-suited for complex nonlinear problems, though it requires extensive data and longer training times. The benefits of ANNs include parallel data processing, the ability to retain data throughout the network, functionality with limited information, and low latency [5]. However, they are more complex compared to k-NN and SVM.

3.2 Unsupervised Machine Learning (USL) : USL algorithms use only input or output data to perform operations and retrieve information, based on identifying common patterns among datasets. These algorithms focus on clustering and dimensionality reduction. The following subsections discuss some USL algorithms used in Visible Light Communication (VLC) systems.

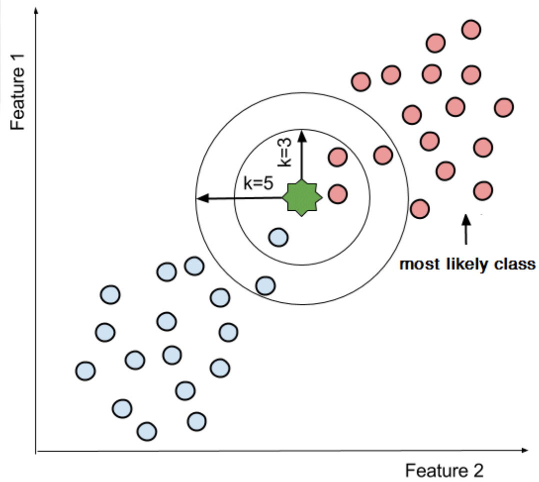

Figure 3: Classification using K-NN

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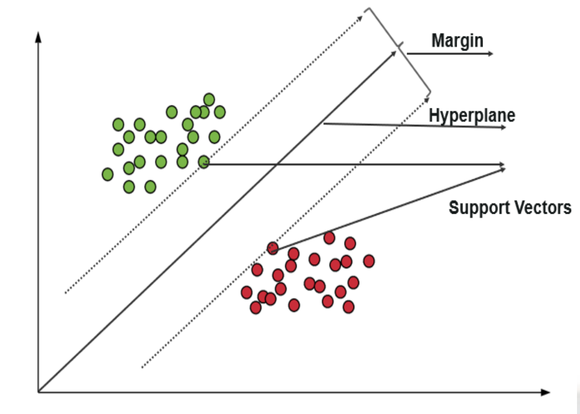

Figure 4: Data Segregation using SVM

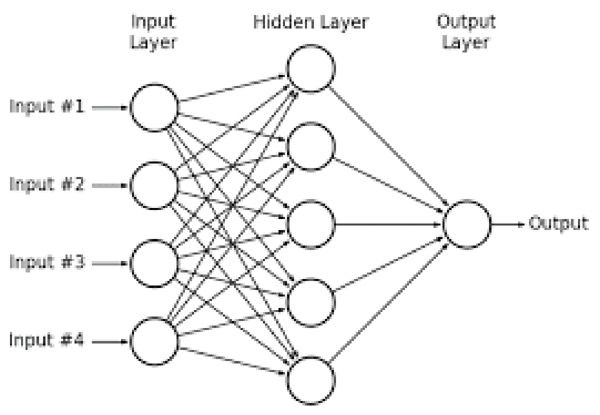

Figure 5: ANN Structure

3.2.1 k-Means Algorithm: This partition-based clustering algorithm categorizes data points into different clusters based on similarity. The primary aim is to select k cluster centers at random intervals. Each data point is assigned to the nearest center using a distance function, and equilibrium is achieved by iteratively updating the centers and reallocating points among clusters [24]. Although straightforward and user-friendly, choosing the appropriate distance function and the number of clusters k can be challenging.

3.2.2 Gaussian Mixture Model (GMM): GMM is a probabilistic clustering method that assigns data to multiple groups based on probability distributions, where data in a group is likely to share a similar distribution [26]. GMM uses several Gaussian distributions, each characterized by a center, covariance (indicating the spread of the distribution), and a mixing coefficient. The optimal values for these parameters are determined through Maximum Likelihood Estimation (MLE). However, since GMM combines multiple Gaussians, determining the parameters for the entire model can be complex and limit its effectiveness.

3.2.3 Density-Based Spatial Clustering of Applications with Noise (DBSCAN): DBSCAN is a density-based clustering technique that forms clusters of high-density points and identifies points in low-density areas as outliers. It uses a threshold to distinguish between core data and outliers (noise) in complex datasets [30]. However, DBSCAN's performance is sensitive to the chosen threshold. This issue can be addressed by using the Ordering Points To Identify the Clustering Structure (OPTICS) method, which considers both data density and spatial relationships.

4. ML Applications in VLC: Visible Light Communication (VLC) has emerged as a promising technology due to its potential benefits over radio frequency communication. However, its application is limited by challenges such as nonlinearity in transmitters and receivers, eavesdropping, channel distortion, and jitter. This section reviews these performance-limiting factors and the ML-based approaches to mitigate them.

Table 1: ML algorithms in nonlinearity mitigation.

Method	Ref.	Outcomes
GMM	[20, 26]	(1) Easy to implement (2) Require small set of variable (3) Higher dynamic range is achieved
k-Means algorithm	[26, 53]	(1) Simple structure (2) Extra learning model not needed (3) Data rate up to 400 Mbit/s is achieved (4) High Q-factor (5) Does not work well with cluster of different sizes and entities
LM algorithm	[33]	(1) Can manage multiparameter frameworks (2) Performance improvement is achieved in the context of training complexity (3) It takes a long time in some scenarios
Gaussian kernel-aided DNN	[34]	(1) Can significantly decrease training iterations up to 47.6%

	(2) Data rate up to 1.5 Gbps
Probabilistic Bayesian-based learning [35]	(1) Compensate for the negative effects of VLC source nonlinearity (2) Improved BER

4.1 Nonlinearity Mitigation: Nonlinear distortion is a major issue in VLC systems, where LEDs exhibit nonlinear transfer functions, meaning their illumination power does not linearly correspond to the control input [26]. This nonlinearity causes significant fading effects and clipping in received signals due to the saturation of photodiodes (PDs) [4]. Machine Learning (ML) models, such as regression analysis, classification techniques, and clustering, can address these nonlinearities by analyzing system parameters using part of the message data as labels. Techniques such as decision feedback equalization (DFE) adjust the current bit based on previous decisions to mitigate distortion and improve bit rates [31, 32]. ANN-based methods also address nonlinearity by leveraging their inherent capabilities. Specific techniques include Levenberg-Marquardt (LM) algorithm-based ANN [33], Gaussian kernel-aided DNN [34], and probabilistic Bayesian-based learning (PBL) [35]. Although ANNs often outperform DFE, their use in VLC is limited due to additional hardware design challenges. Table 1 summarizes key algorithms developed to address nonlinearity in VLC transceivers.

4.2. Security

Security is crucial for any wireless network to prevent unauthorized access to confidential information. Although Visible Light Communication (VLC) systems have a lower risk of eavesdropping compared to other methods, security remains a significant concern, especially in public areas like community centers, malls, and research facilities where information might be accessed by multiple individuals [36]. To enhance VLC security, various methods have been proposed, such as reinforcement learning (RL)-based beamforming. This technique aims to safeguard sensitive information by optimizing beamforming strategies in dynamic situations through an RL-based multiple-input-single-output approach for Markov decision processes [37]. Deep reinforcement learning is also employed to improve convergence rates and learning in anti-eavesdropping networks, particularly in large and complex environments. Additionally, artificial noise-based linear precoding is used to increase secrecy rates by utilizing truncated discrete generalized normal distributions [38]. Although physical layer security (PLS) techniques for VLC, including secrecy outage probability and secrecy capacity, are not covered in this review, interested readers can refer to [36] for more details on PLS in VLC.

4.3. Channel Estimation

In VLC systems, data is transmitted using the visible spectrum (430 THz to 790 THz) through LEDs with intensity modulation/direct detection (IM/DD), and photodiodes (PDs) capture signal fluctuations to convert them into digital format. Accurate channel modeling is critical for reliable and error-free signal transmission. However, the channel's behavior can be difficult to predict due to factors like unknown reflective surfaces, noise variations, and moving objects [10]. Machine Learning (ML) is effective for measuring the correlation between inputs and outputs in VLC networks, especially when relationships are nonlinear. For instance, a deep neural network (DNN) algorithm developed in [11] learns transmission medium features by labeling message data and using receiver data samples. This DNN approach outperforms least squares (LS) and minimum mean square error (MMSE) methods in bit error rate (BER) without complex calculations at the receiver. Similarly, an ANN-based network developed in [10] estimates channel properties by considering six input attributes, including refraction, transmitter architecture, line of sight, noise, and transceiver location, achieving up to 97.7% accuracy. An adaptive probabilistic Bayesian learning (PBL) method in [12] provides a reliable and efficient means for real-time indoor VLC channel detection, while a Bayesian compressive sensing approach in [13] predicts reflective transmission distances in underwater VLC, improving prediction accuracy and reducing pilot overhead. Table 2 summarizes the ML algorithms used for VLC channel estimation and their results.

Table 2: ML algorithms in channel estimation.

Method	Ref.	Outcomes
ANN	[10]	(1) Simple to use (2) Precision level of up to 97.7% can be obtained
Adaptive PBL	[12]	(1) Can estimate real-time indoor VLC channel (2) Require less training time (3) Decrease calculation complexity
Bayesian compressive sensing	[13]	(1) It can be used to predict underwater VLC channels (2) Enhance efficiency

		(3) Increase prediction correctness
DNN	[11]	(1) Improve BER without requiring any complicated calculations (2) It has BER performance superior to LS and MMSE algorithms

4.4. Location Tracking

As mobile Internet usage grows, location-based services (LBS) have become crucial for precise positioning and routing. Accurate indoor positioning is more challenging compared to outdoor settings due to radio communication properties and complex indoor environments. VLC-based indoor localization has emerged as a viable method, offering high reliability and non-intrusiveness compared to traditional radio frequency techniques.

VLC-based positioning also provides benefits such as low cost, durability, and renewability, making it an efficient indoor localization option [28]. Despite these advantages, issues like signal distortion, scattering, and noise can affect positioning accuracy. To improve location accuracy, various ML algorithms are explored, including photodetector (PD)-driven and sensor-based tracking methods.

PD-Driven Tracking: PD-driven techniques use parameters such as travel time, incident angle, and received signal strength (RSS) for indoor positioning with VLC systems. RSS-based methods can be categorized into geometric and fingerprint-based techniques [39]. In ML, both single and multiclassifiers are used for positioning. For instance, wk-NN is used to position the receiver accurately by calculating the weighted Euclidean distance between nodes [14]. Other models, such as 2nd-order regression and polynomial trilateral models, also show improved positioning accuracy [40]. Additionally, fingerprint-based databases using wk-NN and k-NN are explored for precise positioning [15, 16]. Comparisons of ML algorithms like SVM, random forest (RF), k-NN, and decision tree (DT) show that SVM offers the highest location precision, while k-NN has the shortest calculation time [17].

ANNs are used to link RSS with receiver location, improving location precision to a mean error of 6.39 cm [23]. Clustering techniques, including LED luminary-based clustering and k-means combined with linear regression, are also investigated for positioning accuracy, with varying results [42, 43]. Combining classifiers, such as extreme learning machine (ELM), RF, and k-NN, offers improved precision and reliability, achieving less than 0.05 m accuracy in 85% of cases [44].

Two-layer fusion networks (TLFN) further enhance accuracy by integrating predictions from different classifiers, resulting in a mean precision of 5.38 cm [45]. However, these methods involve complex calculations.

Sensor-Based Tracking: Sensor-based tracking uses incident angle data to estimate LED coordinates and location. Sensor inclination can lead to positioning errors [28]. Research in [46, 47] shows that sensor-based ANNs can effectively adjust for errors caused by sensor inclination, enhancing precision. These methods also require extensive data for training but reduce location estimation time, enabling real-time monitoring. Table 3 provides details on ML algorithms for VLC positioning.

4.5. Jitter Compensation

Jitter, which affects performance by causing signal distortion and estimation errors, is common in VLC networks. Amplitude jitter, particularly in pulse amplitude-modulated (PAM) VLC, impacts the bit error rate (BER). ML algorithms can address jitter in VLC systems. Unlike classification and neural network (NN) techniques, which are less effective, modified density-based spatial clustering of applications with noise (DBSCAN) algorithms can mitigate jitter effects. DBSCAN, a well-known unsupervised ML technique, distinguishes between datasets without needing additional training data [30].

Techniques like IQ-Time DBSCAN and 2D-DBSCAN are used to reduce amplitude variations in QAM16 and PAM8 VLC systems, respectively, improving Q-factors and reducing BER despite high jitter levels [48, 30]. Other studies, such as [49], show that DBSCAN can effectively handle amplitude variations in PAM4 VLC systems, achieving a Q-factor of 2.299 dB to 3.299 dB with 0.12 amplitude variation spectrum.

4.6. Modulation Identification

Nonlinearity in VLC can cause significant phase distortion, making conventional methods for signal judgment ineffective. To address this, cluster algorithms of perception decisions (CAPD) [18, 19] and Gaussian Mixture Models (GMM) [20] are explored to mitigate constellation discrepancies. CAPD, developed through k-means, addresses amplitude discrepancies and performs modulation format detection, achieving improved performance compared to simple linear techniques. Preequalization-based k-means clustering further enhances results, reducing bit error rates (BER) significantly [19]. GMM also provides enhanced performance by grouping successive data based on similarity, although it requires more processing time [22]. Table 4 summarizes the ML algorithms used for modulation identification and their outcomes.

Method	**Ref.**	**Outcomes**
k-NN & wk-NN	[14–17]	(1) The dataset must be modified with the change in transmission medium (2) The models are trained with RSS-based datasets (3) These models outperform conventional methods based on received signal strength (4) [15] Has the best average location accuracy of 4.2 cm (5) Low to moderate efficiency
ANN	[23, 41, 46, 47]	(1) A large amount of sampling data is required (2) Highly reliable after plenty of training process (3) Sensors or RSS-based datasets train models (4) With the LoS component, [41] has the best positioning accuracy of 2.7 cm (5) Useful for real-time location monitoring (6) Highly efficient
k-Means	[42, 43]	(1) Models are trained with RSS-based datasets (2) Moderate reliability (3) Less accurate than ANN and *k*-NN (4) Efficiency moderate to high
Comparison of SVM, RF, *k*-NN,and DT	[17]	(1) Highest location accuracy of 8.6 cm with SVM (2) Shortest mean calculation time of 5.6 cm with *k*-NN
Multiple classifier	[44, 45]	(1) Take advantage of strengths of single classifier (2) Precise and reliable (3) High calculation complexity

4.7. Phase Estimation

Nonlinearities in VLC can lead to severe phase distortions. Conventional constant modulus algorithms may fail to correct constellation coordinates effectively. ML techniques like GMM [26], SVM [50], and k-means [25] are used to mitigate phase distortions. Studies in [26] show that GMM outperforms k-means in QAM16 VLC with lower BER and higher peak-to-peak voltage. In underwater VLC, k-means phase correction reduces BER and increases data rates [25]. SVM is used to evaluate and correct phase distortions in carrier-less amplitude and phase modulation VLC, significantly lowering BER [50]. Table 5 presents the results of ML algorithms for phase estimation.

Table 4: ML algorithms in modulation identification.

Method	Ref.	Outcomes
k-Means algorithms	[18, 19]	(1) [18] Based on postequalization and [19] based on preequalization (2) BER reduced by 10% in [18] and by 50% in [19] (3) Gain improved by a factor of 1.6 dB to 2.5 dB in comparison to linear compensation
GMM	[20]	(1) Can operate on a wide range of bias current and voltage (2) Require more time in execution

Table 5: ML algorithms for phase estimation.

Method	Ref.	Outcomes
k-Means	[25]	(1) Can efficiently improve BER performance (2) Maximum data rate up to 1.4625 Gbps is obtained
GMM	[26]	(1) Low BER than *k*-means (2) Gain is 1 dB higher than *k*-means with 1.5 Gbps bit rate
SVM	[50]	(1) BER can be reduced to 7% with significant correction in phase distortion (2) Data rate up to 400 mbps can be obtained

5. Comparative Analysis

Each machine learning (ML) technique offers distinct advantages and limitations. Some methods are highly accurate but complex, while others are simpler but less precise. The choice of ML approach depends on specific needs, application features, and system capabilities. For instance, k-Nearest Neighbors (k-NN) is a straightforward method with a limited number of parameters, making it easy to implement, but it struggles with high-dimensional datasets [24]. Support Vector Machines (SVMs) are well-suited for problems involving high-dimensional data and linear separability. Their kernel-based approach enables them to handle nonlinear datasets, although selecting the right kernel can be challenging [50]. Decision Trees (DT) are recommended for smaller datasets but can become overly sensitive to imbalances, particularly in complex trees. Random Forests (RF) address this issue by aggregating multiple DTs, though this increases computational complexity [17]. Deep Neural Networks (DNNs) excel in handling nonlinear and complex systems and can operate directly with raw data, eliminating the need for extensive preprocessing. However, they require substantial data and are computationally intensive.

In unsupervised learning (USL), clustering and dimensionality reduction are commonly used. The k-means algorithm is efficient and simple, but its flexibility is limited by the need to predefine the number of centroids. In contrast, Gaussian Mixture Models (GMMs) offer greater flexibility due to their probabilistic nature, though they require complex parametric optimization [26]. Density-based Spatial Clustering of Applications with Noise (DBSCAN) is effective in handling noisy data points due to its density-based approach.

In VLC systems, the choice of ML algorithms is guided by their strengths and system requirements. For nonlinear mitigation, channel estimation, and positioning, Artificial Neural Networks (ANNs) are favored for their strong ability to handle nonlinear mappings. k-NN and multi-classifier algorithms are preferred for location tracking due to their precision. DBSCAN is particularly effective in mitigating random jitter. Clustering techniques are used for phase and modulation estimation because of their ability to group unlabeled data. Table 6 provides an overview of the most commonly used ML techniques in VLC networks.

6. Future Perspective

VLC has achieved significant advancements in the 5G era, yet several challenges remain, particularly related to current optical architectures that hinder network performance. Future research should focus on new design concepts to address system failures and enhance VLC network efficiency. Existing VLC indoor and underwater channels lack comprehensive solutions for precise channel determination, indicating a need for a more thorough analytical network design. The potential of ML in VLC is still underexplored, with considerable interest in its application for input-output mapping, identification, and correlation. Although ML has made strides in fields like image and video processing and AI, its use in VLC is still emerging [27]. Additionally, Convolutional Neural Networks (CNNs) have not been fully examined in the context of VLC networks. Their feature extraction capabilities and structural complexity warrant further investigation to fully harness ML's potential in VLC systems.

Table 6: Comparison of various ML schemes.

ML algorithms	Applications	Ref.	Action position	Characteristic parameters
k-NN	Positioning	[14–17]	Receiver	Supervised, moderate complexity
SVM	Phase estimation	[50]	Receiver	Supervised, moderate complexity
ANN and DNN	Nonlinearity mitigation, positioning, and channel estimation	[10, 11, 23, 33, 41, 46, 47]	Receiver	Supervised, high complexity
Multiple classifier	Positioning	[44, 45]	Receiver	Supervised, high complexity
k-Means	Nonlinearity mitigation, positioning, phase estimation, and modulation identification	[18, 19, 25, 26, 42, 43, 53]	Transmitter and receiver both	Unsupervised, low complexity
GMM	Modulation identification and phase estimation	[20, 26]	Receiver	Unsupervised, moderate complexity
DBSCAN	Jitter compensation	[30, 48, 49]	Receiver	Unsupervised, low complexity

Future Research Challenges

Several significant research challenges in VLC that need to be addressed in the future include:

(i) **Real-Time VLC Transmission:** Real-time VLC transmission requires datasets and training that reflect real-time conditions. Since channel behavior in VLC can change over time, current ML techniques often rely on offline data. Future developments should focus on integrating self-learning, adaptive, and optimization capabilities to handle real-time scenarios effectively [51].

(ii) **Frequency Band Constraints:** VLC networks are typically limited by the narrow frequency bands of the light sources used. To overcome this limitation, ML techniques designed for high illumination could be employed to enhance system performance [4].

(iii) **Multi-Input and Multi-Output VLC:** While VLC has traditionally used single LED and photodetector (PD) setups for line-of-sight communication, there is a growing trend towards using arrays of LEDs and PDs for multi-input and multi-output transmissions. ML applications could significantly improve performance in these advanced VLC setups [51].

(iv) **Channel Modeling:** There is a need for better channel modeling in VLC systems to account for various indoor surfaces and their effects on refraction, reflection, and scattering, as well as higher-order non-line-of-sight (nLoS) components, geographical illumination distribution, and noise. Future research should focus on developing smart ML models to address these complexities [27].

(v) **Advanced Modulation Techniques:** Current ML-based VLC systems often use modulation techniques like M-PAM (where M = 4, 8, 16), CAP-MQAM, and CAP-QPSK. To boost data rates and energy efficiency, incorporating more effective modulation methods such as probabilistic constellation shaping and geometric constellation shaping could be beneficial [52].

(vi) **Location-Based Services (LBS) in IoT:** ML can significantly enhance location-based services in IoT applications using VLC. Efficient route design for indoor positioning is crucial for quality of service (QoS). ML classification models, particularly artificial neural networks (ANNs), are particularly effective for precise location tracking [39].

Conclusion

This paper has reviewed various ML algorithms aimed at reducing computational complexity in indoor VLC transmission and enhancing network performance through different design requirements. Each ML approach has its unique advantages and limitations. For real-time applications, careful consideration of individual needs, system features, and resource availability—such as computational complexity and device nonlinearity—is essential. Based on the current literature, it is clear that the application of ML in VLC is still developing. Further research into ML techniques for diverse real-time VLC scenarios is necessary to advance the field and support the evolution of VLC technology in the 5G era and beyond.

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