Improved BER Performance using Novel ELM based demodulator for CAP-VLC System

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ABSTRACT Recent trends in the field of communication science show that most devices are built and governed by Visible Light Communication (VLC) and Light Emitting Diodes (LED). The communication process depends on source characteristics and bandwidth restriction, and effective methods of modulation and demodulation can enhance data rate. Attractive and practical Carrierless Amplitude-Phase (CAP) modulation is used for higher efficiency and easier implementation. However, the performance of the CAP-VLC system gets adversely affected by factors like jamming, scattering, and low sensitivity to receiver signal. Hence, this paper examines the mitigation of available system degrading factors, based on a high-speed, extreme learning machine algorithm (ELM). Prediction analysis and simulation are processed using trained raw dataset for CAP demodulation, to prove the level of performance in terms of accuracy as 92%, under various parametric conditions. This system that is proposed can achieve bit error rate (BER) of 40% to 50% of noise ratio and can be effectively used in sectors like medical health care, banking, and finance.

INDEX TERMS Carrierless Amplitude and Phase Modulation, Extreme Learning Machines, Light Emitting Diode, Nonlinear Equalizer, and Visible Light Communication

I. INTRODUCTION

The rapidly emerging, huge volumes of mobile and edge devices have lead to the shortage of bandwidth and we are faced with a bottleneck in our attempts to enhance network capacity. While Visible Light Communication is the latest technology that can support the next-generation network [1], the VLC attocell network is a combination of communication and lighting for a large indoor environment. For optical communication, different types of light-emitting diodes (LED), transmitters and photodiodes, and receivers are employed [2]. The inexpensive and most widely held LEDs for the currently active communication system are phosphorescent layered, blue light LEDs. These LEDs chips alter the blue light component into yellow, which, together with the blue one, generates a white spectrum [3]. A significant characteristic of commercial LED is its restricted bandwidth that gives a higher transmission data rate together with the modern, modulation technique adaptation. Among these, CAP modulation predominantly uses the VLC system for its simplicity, lesser complexity, and greater accuracy [4] [5]. The indoor VLC system is most widely used one because of its efficient and fast transmission. In [6] says about the Centralized Light Access Network (C-LiAN) for indoor local communication with central pool and centralized controller called cloud radio access network. Centralized access has many advantages like customised problem finding, easy and fast communication via cloud random access network (C-RAN) and points to enable signal processing. Implementation of C-RAN can reduce cost and complexity. In another way the indoor VLC system can also be combined with the conventional RF system via reconfigurable intelligent surface (RIS) in order to show the performance of outage probability and BER. Reflecting meta-surface N plays the main role on the performance analysis. If N is low, then high mismatch is observed between simulated and analytical result, [7] otherwise N could be high. Apart from communication and illumination, secrecy can also be maintained by using secrecy outage probability (SOP) [8] with RIS, and by quantifying
the gain of the signal obtained using RIS concerning SOP. Linear power amplifiers (PAs) in an indoor VLC system, require modulated signals with low peak amplitude to power ratio (PAPR). But the PAs have more efficiency in power level during the non-linearity part, which lies in saturation. The data output from the VLC channel has a significant nonlinear distortion. Adding an equalizer to the demodulator will balance the effect of nonlinear distortion [9] [10] [11]. When the non-linearities are higher, linear and nonlinear equalizers are employed [12]. When the system employs good complementary equalizers, it may acquire a reasonable convergence rate and fewer error rates. The equalizer helps the system to get proper illumination as well as power distribution for effective communication. The variation in LED lamps and the neural network characteristics proves the better performance of the VLC system. [13] CAP-VLC systems are implemented with algorithms such as Support Vector Machines [14], K-Nearest Neighbourhood (KNN) [15], Artificial Neural Networks (ANN) [16] [17] and even Machine Learning Algorithms [18] [19]. Yet, learning-based CAP-VLC systems require a brighter side of research to overcome the challenges mentioned above. In this paper, a new modulation technique proposes the intelligent data-driven framework shadowed by ELM; a new methodology of creating datasets, using a simulated environment, and discusses various experimentations that use open simulated datasets. The research responsibility is being shared 1. This paper proposes the new data-driven CAP-VLC simulated environment to collect available data sets that are used to study the characteristics of the receiver end of the CAP-VLC demodulation technique. An open dataset for CAP-VLC systems was genuinely taken. 2. The proposed system demodulator is designed using High-Speed Feed-forward Neural Network. The working principle of extreme learning machines (ELM) is deployed in the proposed neural network, with 15 hidden layers and 100 neurons. Then modulation features were extracted to implement the ELM-based intelligent CAP demodulators. 3. This paper also shows the design of reconfigurable and scalable CAP-VLC software test beds, to extract 302500 raw datasets which can be used for experimentation. Moreover, the main objective in designing software test beds is, to reduce the cost and computational complexity. 4. Based on the data collected and model designed, various machine learning algorithms such as SVM, KNN, and ANN along with the proposed Extreme Learning Machines were investigated at different scenarios such as distance and receiver parameters concerning SNR. Analysis simulation of the proposed ELM at the demodulator shows higher accuracy than at other demodulators. The structure of the paper is as follows: Section II is what is inferred from the related works. Section III is a brief of the CAP modulation. The system model has been explained in Section IV. The proposed methodology is composed in Section V. Result analysis and discussion are demonstrated in Section VI. The Conclusion, along with future scope, is presented in Section VII.

II. RELATED WORK
Shuai Ma et. al [16] designed an end-to-end, data-driven demodulation mechanism and they have collected received data, with different modulation schemes, in a real physical prototype model. The system works with a real modulated dataset and measures the transmission distance from 0cm to 140cm. Convolutional Neural Network-based demodulators are employed here. Double Boosted Network and Restricted Boltzmann Machines are used by them to extract the modulation features. This makes the system more complex and impractical. But its accuracy is high in short distance or high SNR scenarios. Adaboost demodulators show the best accuracy when compared with other demodulators and they prefer high order demodulation. Guoqiang Li et. al [17] shows the mitigation of linear distortion by using a Volterra model linear equalizer, and Distributed Neural Network (DNN) with a linear equalizer. Both linear and nonlinear distortion has occurred in this system. Our experiment helps us reveal that the above mentioned method effectively support linear distortion but is not suitable for nonlinear distortion. However, Volterra and DNN are not much supportive of nonlinear distortion. Qing Wang et al [18] show that the performance of indoor visible light communication can be estimated by correlated color temperature (CCT), but then illuminance is not a proper factor for estimation. It can be proved that image transformation can enhance performance. G. E. Hinton and R. R. Salakhutdinov [19] show the theoretical concepts of converting the image and reducing its size so that the speed of training in ML is high. The reconstruction of high dimensional input vectors is made easy. In autoencoder network, gradient descent is utilized for adjusting the weights, for the improvement of the framework. PCA (principal component analysis) has been utilized in earlier cases to reduce the dimensionality of information, but the effect of gradient descent is more in such cases. Shengliang Peng et.al [20] detailed some of the ML mechanisms like CNN, ALexNet GoogLeNet to show the effect of reduced, vanishing gradient and the improvement made, using computer vision mechanism. To show the improvement in the entire ML system, the author has decided to use two main characteristics - sparse connectivity and parameter sharing. Unlike in DL-based systems, in ML-bassed systems the computation complexity is more as the iteration is more. Here, the system features increase, or the SNR decrease, makes the system complex and slower in implementation. Sanqing Hu et.al [21] have used Support Vector Machines (SVM) for feature identification, by finding an optimal hyperplane. The feature separation can be done by SVM as line, plane, and hyperplane. SVM detects the spectrum availability as the features are considered as received signal strength. This increases the detection probability. But it is limited to physical layer protocol identification. Hurmat AliShah et.al [22] show the transmission of waves by combining two levels of spectrum, using altered KNN. The spectrum limitation is not adaptable for huge networks, but it is suitable for small cognitive radio networks. The survey of different ML-based
algorithms is suitable for short distance, linear or nonlinear distortion, mitigation and reduced channel interference. The proposed ELM-based demodulators have receiver parameters and the raw dataset to perform a novel ML-based equalizer, at the CAP-VLC demodulator. This improves the BER performance of 40% to 50% under m-CAP modulation.

III. CAP MODULATION

CAP modulation, which was proposed by Bell Lab in the 1970s, is another sort of staggered and measurement-based modulation innovation. Limited bandwidth spectrum, with reduced system complexity, to achieve high data rate and spectral efficiency, may be possible by utilizing CAP modulation. In CAP modulation, the electrical or optical conversion is no longer required because it utilizes two symmetrical digital filters. So, CAP modulation does moderate system complications expressly and doesn’t rely on a carrier for transmission. [17] Machine Learning Algorithms are widely implemented for better performance of the entire VLC system with more accuracy, distortion free transmission, responsibility, better BER, and so on. With the help of this latest technology, today’s communication can be well established in many applications.

IV. SYSTEM MODEL

A flexible, end-to-end VLC system is shown in figure 1. As suggested in figure 1, the self-generated digital signal \( v(n) \), which is considered as \( \ldots 1010100 \ldots \), is modulated using CAP modulation in the base of Quadrature Amplitude Modulation (QAM) scheme. With the filter size of 31 and the tap value of 3 or 5, the system performance can be improved. The real part of the signal is fed to LED and wireless channels. These signals will get added with a bias, for the balancing system, before the transmission. But the addition of forward current and DC bias introduces non-linearity in the transmission signal. Also, this addition of DC bias, leads to greater device bandwidth. The digital modulation in this paper comes out with \( X(t) \) as follows,

\[
X(t) = Re\{v(t) * g(t)e^{2\pi ft}\}, 0 < t \leq T
\]

The simulation is proposed with four LEDs as its source. Among these, the distance between the LED concreated on the ceiling is 170cm x 4 and its semi-half degree angle \((\phi_{1/2}) = (7.5 \pi) / 180\), to mark the exact converging point towards the receiver. To get the proper power at the transmitted signal, luminous intensity and the allocated transmitted power are very important. Interference may occur, if intensity or power gets changed slightly. At the detector point, the optical signals, with additive white Gaussian (AWG) noise filter, are down sampled. The refractive index of the concentrator \( \rho \) is calculated as \((4.2366e^{-05} + noise) / 0.4W\) respectively. The size of the filter and tap value is the same as in the transmitter. Then, the synchronized signal is fed to the pre-equalizer, to mitigate linear distortion. After CAP demodulation and decoding, the original signal can be received.

An optimum equalizer coefficient can be found using the least mean square (LMS) algorithm which is very efficient and demanding in the communication field. LMS is used efficiently to mitigate linear distortion. But, during the optical-electrical and electrical-optical conversion, non-linear imbalance may occur, and adding small bias for positive normalization will introduce non-linear distortions. To maintain the accuracy and reduction of noise, the proposed ELM is implemented. Implementation of proposed ELM utilizes randomly collected dataset from the Matlab design, as per the parameters from table 1. Maintaining the distance constant in random position \((50cm, 100cm, 125cm, \text{ and } 150cm)\), and from table 2, with the labelled parameters such as light intensity as 24 lux, received power as \(4.23e^{-05}W\), detector angle as 0.359, the distance between transmitter and receiver, from 85cm to 115cm, are varied. SNR running under 100 iterations, for continuous thirty days, are found to show the better BER performance of proposed ELM based demodula-

| Table 1: Transmitter specification used in CAP-VLC model |
| --- |
| Parameter | Dimension |
| Distance between LED | 170 cm |
| Semi-half degree angle \(\phi_{1/2}\) | \((7.5 \pi) / 180\) |
| Power transmitted \(P_t\) | 0.1W |
| Centre luminous intensity \(I_0\) | 24 |
| Reflection factor of the wall \(\rho\) | 0.1 |
| Unit of LEDs | 400 |
| Angle of incidence \(\Phi_i\) | \(\text{atan}(\text{xydist}.* \text{heightLED})\) |
| Angle of irradiance \(\phi_i\) | \((7.5 \pi) / 180\) |
| Array of LEDs | 4 |

| Table 2: Receiver specification used in CAP-VLC model |
| --- |
| Parameter | Dimension |
| Photodiode responsivity \(R\) | 0.55A |
| Refractive index of optical concentrator \(i\) | 1.46 |
| Gain of optical filter \(T_s\) | \(P_{x, total} / P_{LED}\) |
| Detector area of PD (APD) | 7.8e-4 m² |
| Power received \(P_{rx}\) | 4.2366e-05 |
| Detector angle \(\Phi_{dc}\) | \((20^\circ) / 180\) |
| Data rate | 115200 |

As shown in figure 1, the design specifications employed in the CAP-VLC system transmitter and receivers are tabulated in table 1 and table 2.
tor in CAP-VLC system. The low, moderate, and high values of BER, SNR, and classes are figured in table 3.

### V. ELM-THE BASIC PRINCIPLE

The neural network plays a vital role in prediction problems. In terms of time-cost density, ELM as a single layer, high-speed, feed-forward, neural network is more efficient than other neural networks such as gradient-based network and back propagation ANN. The intricacy of such networks is that, training complexity in terms of parameters updation and concealed neurons are retrained several times, which increases the time complexity at runtime. To overcome this, Huang et.al developed a low-complexity network named single-layer feed-forward network, or ELM [23]. The parameters of the proposed neural network are generated randomly and need not be tuned at runtime. The prediction exactness, planning velocity and incredible speculation are enhanced to the global optimum. One of the major applications of ELM algorithm in the communication field is spectrum prediction. In this aspect and as we got motivated, ELM can be utilized for designing the demodulator, based on the VLC. We are concerned with the application of ELM and proving the design of the system from the motivation point of view. In our research work, spectrum prediction of ELM is not related.

### A. PROPOSED METHODOLOGY

The proposed methodology used in the research work is shown in figure 2. The proposed novel ELM contains different levels in its model such as System Model (Transmitter and Receiver), Feature extractions and implementation of ELM-based demodulation. The working mechanism of every phase is discussed in the preceding section. The software was developed using MATLAB R2018 versions which run on Intel i7 CPU with 8GB RAM, 1TB HDD and it was used for collecting data with different features at various scenarios of distance, SNR, BER and changes in modulation schemes. The software developed can be reconfigured for any modulation scheme and be scalable for getting the input vectors. As for the labelling of high SNR and low BER with the extracted features of SNR, modulation index, types of modulation, power, intensity of light and original data transmitted, with the condition of BER, if the SNR is high we have labelled it as 1 and if SNR is low it is labelled as 0.
B. PROPOSED ELM BASED DEMODULATOR

ELM network comprises only three layers in terms of input, output, and concealed layers. The mathematical output formation of the proposed ELM predictor is given below.

\[ \mu(t) = \sum_{i=1}^{\alpha} u_i \rho_i(t) = \rho(t)u \]  

(2)

\[ \mu(t) = \sum_{i=1}^{\alpha} u_i \rho_i(t, c_i, d_i) \]  

(3)

In this network, \( c \), \( d \) are input weight vector and concealed layer node activation function parameters, with ‘\( \alpha \)’ number of nodes in the concealed layer. ‘\( t \)’ and \( u = [u_1, u_2, \ldots, u_\alpha]^T \) represents the input vector layer and the output weight vector respectively. The basis activation function of the output vector is denoted as \( \rho(t) = [\rho_1(t), \rho_2(t), \ldots, \rho_p(t)] \) where ‘\( p \)’ denotes the number of output vector in basis function (2). In this analysis we impose Gaussian function as the activation function. Gaussian function has a fast decaying property as it is a localized function from the center of its location. Assuming N hidden node number pair as data training set \( \{t, \beta\}_1^N \), equating with (3) gives us,

\[ \sum_{i=1}^{\alpha} u_i \rho_i(t_j, c_i, d_i) + qt_j + y = \beta_j, j = 1, 2, ..., r \]  

(4)

Accuracy can be improved by reducing the localized effect, using addition of linear neurons as shown in (4).

\[ \theta = \begin{pmatrix} \theta(t_1) \\ \theta(t_2) \\ \vdots \\ \theta(t_N) \end{pmatrix} \]  

(5)

where \( \theta = \rho_i(t_j, c_i, d_i) \) represents the concealed neurons, Equation (4) can be rewritten as, \( u^T \theta = \beta \) and the optimal result of this equation on the output weight is

\[ u^* = \theta^* \beta = \theta^T \left( \frac{1}{C} \theta \theta^T \right)^{-1} \beta, \beta = [\beta_1, \beta_2, \ldots, \beta_N]^T \]  

(6)

The parameters such as weights and bias values between input and concealed layer, are randomly generated and the output synapses are obtained through the Moore-Penrose pseudoinverse method (Least -square method). Though the entire process is auto tuning, \( C \) acts a constant for fine tuning the model. \( \theta^* \rightarrow \) reciprocal of \( \theta \), the output matrix on concealed layer as Moore-Penrose generalized inverse matrix.

\[ \mu(t) = \theta(t)u^* = \theta(t)\theta^T \left( \frac{1}{C} \theta \theta^T \right)^{-1} \beta \]  

(7)

where \( \beta \) denotes the output score lies between concealed layer and output layer.

ELM utilizes the part capacity, to yield great exactness for better execution. The significant focal points of the ELM are negligible preparing blunder and better guess. Obtained from the Matlab source, input assigned to the extreme learning machine is 302500 raw trained data. Since ELM exploits auto-tuning of the weight predispositions, and non-zero initiation capacities, the related applications are found as arrangement and expectation esteems. [23]. For the creation of the dataset, additive white gaussian noise level is utilized to test the distortion and the impact. To analyze the BER performance, concerning white gaussian noise, ELM yields the equalized output for the VLC system. The information vectors which are determined on the collector side, are taken to the system for additional computation.

VI. RESULT & DISCUSSION

The proposed system model has been used for extracting the features from the received signals which are then used to train the proposed ELM architecture. For effective data collection and feature extraction, we have designed a simulation environment that can be adaptive to the different environments. For the features which are extracted to train the proposed ELM-based demodulator for nearly 302500 raw data, and to assess the presence of the proposed algorithm, we have taken the datasets in the proportion of 80% as training and 20% as testing. The presentation assessment of the proposed algorithm can be determined by the scientific articulations which are given below as performance analysis:

\[ \text{Accuracy} = \frac{OR}{T} \times 100 \]  

(8)

\[ \text{Precision} = \frac{RP}{RP + RN} \times 100 \]  

(9)

\[ \text{Recall} = \frac{RN}{RP + RN} \times 100 \]  

(10)

where \( RP \) and \( RN \) represent real positive and real negative values, \( OR \) & \( T \) represent the number of observed results and the total number of iterations. To prove the strength of the algorithm, it has also been validated with open-source datasets [24] and comparisons are made with other algorithms. Table 4 presents the comparison of various machine learning algorithms for different categories of input datasets.
From table 4, the observed accuracy level of the proposed algorithm is 92.86% from software testbeds, and 92.5% from the hardware testbeds which prove that the performance of the new algorithm is maintained with RMSE less than 0.03 which outperforms the other machine learning algorithms. The proposed ELM is made of single layered neural network system in which parameter specification from table 1 & 2 are utilized with dimensional space, dataset, number of input vectors, number of concealed neurons, number of output vectors, tuning of weight, and bias. The proposed ELM can support both lower and higher order modulation. We have optimized the learning algorithm through classification function which is to be Gaussian and fix the k-fold with the concealed neurons of 200. This made the proposed ELM algorithm performed better than any other algorithm.

| Table 4. Comparison between different ML demodulators with the proposed ELM demodulator |
|----------------------------------|------------------|
| **Dataset Details** | **Algorithms Used** | **Performance Metrics Measured** |
|-----------------|-----------------|---------------------------------|
| Labeled data | SVM & ANN | Accuracy % | Precision % | Recall % |
| Labeled data | KNN | 87.2 | 80.4 | 81.5 |
| KNN | ELM | 92.7 | 93.4 | 92.8 |
| ELM | 92.5 | 93.4 | 92.8 |

Moreover, the table 4 clearly shows that the developed software can also be used as the testbeds equivalent to hardware testbeds which can readily reduce cost and computational complexity. After evaluating the performance of the proposed learning algorithms, the network characteristics of the ELM-demodulator-based CAP-VLC systems were analyzed at different distances. Table 5 shows the network parameter comparison and the accuracy performance, with different levels of parameter changes concerning k-fold value, k value, epochs, and concealed neurons.

The comparison of computational complexity is as shown in table 6. Presence of overhead in the classification and regression model reflects their computational complexity. As the overhead occurs in correspondence to the increase in dataset and with algorithm change the complexity increases. This problem is limited by utilizing proper kernel function. Proposed ELM has negligible overhead in their mechanism, and so, the computational complexity is also less. Computational complexity is proved by Big-O-notations. Proposed ELM has proved its computational complexity in terms of \( O(n^{k_1 - 6}) \), where \( n \) is the number of neurons and \( k_1 - 6 \) represents the number of layers. Value of computational complexity is based on the number of layers. As the number of layers increases, the computational complexity also increases.

In this proposed work complexity of other algorithms like SVM, ANN and KNN are considered for simulation and comparison as \( O(n^{k_1}) \), \( O(n^{k_1 \times m^{k_1}}) \), and \( O(n^{k_1 + 2/h}) \) respectively. Because, the SVM algorithm supports for simple and small patterns that are easy to interpret with less complexity. Considering KNN, it has \((n+m)\) layers in this experiment which shows the computation is more complex and so the output is challenging to interpret. Then by having ANN for experimentation, it has nominal function of \( k_1 + 2/h \) per concealed layer section. So, the computation is moderate and the pattern complexity is reduced comparatively. Our proposed ELM has \( k_1 - 6 \) layers that show very less usage for its better performance and the interpretation is made easy with less complexity. The complexity is directly proportion to the number of layers.

| Table 5. Comparing network parameters of different algorithms |
|-----------------|----------------|----------------|----------------|
| **Metric** | **SVM** | **KNN** | **ANN** | **ELM** |
| Kernel | Linear | Support vector | Gaussian | Linear |
| Euclidean distance | Levenberg-Marquardt | Euclidean distance | Gaussian |
| Iteration | 100 | 100 | 100 | 100 |
| Samples | Labeled data | Labeled data | Labeled data | Labeled data |
| Epochs | 50 | 50 | 50 | 50 |
| Training/testing | 80:20 | 80:20 | 80:20 | 80:20 |
| Neurons | 100 | 100 | 100 | 100 |
| Accuracy (%) | 87.8 | 87.2 | 88.4 | 90.4 |

**Table 6. Comparison of computational complexity**

| Classifier | Overhead | Function | Computational complexity |
|-----------|----------|----------|--------------------------|
| SVM & ANN | Present | Linear | High |
| KNN & ELM | Present | Gaussian | High |
| ANN & ELM | Present | Quadratic | High |
| SVM & ANN | Present | Linear | High |
| SVM & KNN | Present | Gaussian | High |
| SVM & ELM | Present | Linear | High |
| SVM & KNN | Present | Gaussian | High |
| SVM & ELM | Present | Linear | High |
| SVM & KNN | Present | Gaussian | High |
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| SVM & KNN | Present | Gaussian | High |
| SVM & ELM | Present | Linear | High |
| SVM & KNN | Present | Gaussian | High |
| SVM & ELM | Present | Linear | High |
| SVM & KNN | Present | Gaussian | High |
TABLE 7. Comparison of BER for four different algorithms – variable distance and changing SNR with different modulation

| Distance | SVM | KNN | ANN | Proposed ELM |
|----------|-----|-----|-----|--------------|
| 50cm     | 0.5e-2| 0.7e-2| 0.2e-1| 0.1e-2 |
| 100cm    | 0.2e-2| 0.4e-2| 0.2e-1| 0.1e-2 |
| 125cm    | 0.1e-2| 0.2e-1| 0.1e-2| 0.1e-2 |
| 150cm    | 0.5e-1| 0.4e-1| 0.2e-1| 0.1e-2 |

increases but the other machine learning based demodulators such as SVM, ANN and KNN have shown very low performance at high SNR and at increased distance. The significance of 32-CAP-VLC system shows poor performance of BER as $10^{-3}$.

When the index is 64, the BER performance of proposed

TABLE 8. Cumulative performance metric

| No. of Training data ratio | Accuracy% | Precision% | Recall% |
|---------------------------|-----------|------------|---------|
| 80:20                     | 92.86     | 93.4       | 92.8    |
| 70:30                     | 90.64     | 91.22      | 91.5    |
| 60:40                     | 89.51     | 90.9       | 90.15   |

FIGURE 3. Performance analysis of different ML based demodulators using 16-CAP-VLC systems (a) Distance = 50 cm (b) Distance = 100 cm (c) Distance = 125 cm (d) Distance = 150 cm
FIGURE 4. Performance analysis of different ML based demodulators using 32-CAP-VLC systems (a) Distance =50 cm (b) Distance =100 cm (c) Distance =125 cm (d) Distance =150 cm

FIGURE 5. Performance analysis of different ML based demodulators using 64-CAP-VLC systems (a) Distance =50 cm (b) Distance =100 cm (c) Distance =125 cm (d) Distance =150 cm

ELM shows better result in all cases as shown in figure 5. But as far as the order of modulation is concerned, 64-CAP modulation is better suited for ELM. Because for various distance of 50cm, 100cm, 125cm, and 150cm it shows less error rate beyond $10^{-5}$. ELM better suited for 64-CAP modulation with the transmitter and receiver technical parameter specifications shown in table 1 & 2. The BER differences are shown clearly in table 7. The significance of 64-CAP-VLC system shows better performance and low error rate beyond $10^{-5}$ with increased distance and SNR. The best-performed output is from the system which explodes with less bit error rate as shown in figure 5 (a), (b), (c) & (d). When compared to other CAP modulation indexes, figure 5 of all distance which are experimented can show bit error rate of 75% increase.

The significance of 256-CAP-VLC system in figure 6, with the distance of 125cm, shows low error rate when compared to other distance and algorithms. Figure 4 & 6 (a), (b), (c) & (d) shows the same response in its bit error rate under the constraints of high SNR and increased distance. From all the above figures 3, 4, 5, & 6, it is clear that the proposed ELM has outpaced the other machine learning algorithms even when the order of modulation increases concerning SNR and distance.
machine learning systems. The simulation results show that ELM based demodulator has outperformed other ML-based systems in terms of accuracy, precision, and recall of 92.7%, 93.4%, and 92.8%, respectively. Even the proposed ELM-based CAP-VLC system has maintained better BERs of 92.4% than all other ML-based demodulators at higher SNR of 10dB and with varying distances (50cm, 100cm, 125cm, and 150cm). Also, it clearly shows that the proposed ELM-based demodulator fits the n-CAP-VLC systems in a better way. The performance accuracy can be improvised further by the usage of self-adaptive, deep learning algorithms, for higher-order CAP-VLC systems.

VII. CONCLUSION

In this paper, High-Speed Extreme Learning based demodulators are intended as connecting users of CAP-VLC systems. A scalable and reconfigurable software testbed is designed and simulated for data set collection and feature extraction. By using the proposed ELM algorithm, nearly 302500 raw trained datasets are preferred for predicting the class values which consist of the different orders (16, 32, 64 & 256) of CAP modulated signals. Comparatively, index value of 64 CAP modulations shows better BER between $10^{-5}$ and $10^{-6}$ than the other three modulations like 16, 32, and 256. Based on the datasets created, we compared and analyzed the proposed ELM demodulator with the other existing

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