International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Deep Learning CNN-Based Hybrid Extreme Learning Machine with Bagging Classifier for Automatic Modulation Classification

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Submitted: 07/08/2022 **Accepted:** 13/11/2022

Abstract: Automatic modulation classification (AMC) becomes the important process in the various communication systems including commercial, telecommunication and military applications. Further, the accuracy of AMC impacts the performance of these applications. Various machine learning approaches were developed to improve the performance of AMC. However, they failed to classify the different modulation schemes, which needs to satisfy all the spectrum requirements under multipath fading environment. Further, the conventional methods are suffering with computational complexity in training to satisfy the real-time operational requirements.So, this article focuses on implementation of extreme learning machine (ELM) for reduction of training complexities and improves the classification performance. Initially, deep leaning convolutional neural network (DLCNN) model is introduced for extracting the inter dependent modulation features based on different modulation types. Further, the hybrid ELM with bagging (HELM-B) classifier is used to classify the various modulation types, i.e., families. The simulation results shows that the performance of proposed AMC system is superior to the conventional AMC systems with an accuracy of 99.15%, and F1-score of 98.73%, respectively.

Keywords: *automatic modulation classification; extreme learning machine; convolutional neural network; deep learning.*

1. Introduction

Real time mobile, satellite, and military communications [1]needs higherdata rates, improved spectrum efficiency, energy efficiency and reduced error rates, synchronization issues [2]. All these are requirements were easily satisfied by selecting appropriate modulation scheme. Further, selection of the modulation type mainly depending on the carrier frequencies, offset values, signal to noise ratio (SNR) levels, transmission rate, and bandwidths under different channel conditions. So, manual modulation selection schemes [3] are failed to select all these parameters at a timeand they failed to enhance the transmission efficiencyin an attempt.

The 5G and future generation communications needs to perform the constraint specific modulation operation. Therefore, the manual selection of modulation class is difficult, which needs to satisfy the higher data rates with effective bandwidth utilization. Therefore, the AMC is used to meet these requirements in the future generation communications.So, AMC plays the crucial role in this process and AMC is used to properly categories the modulation types in order to get the best results. In most commercial systems, the receiver may make acknowledgement signals about the modulation scheme of the signal being delivered. The conventional AMC systems [4] are utilized this received signal for classification purpose.Butit is impossible to precisely predict the communication characteristics of receivers in military applications.Further, the received signals in military communications are affected by the jammers.

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Recently, modulation systems are focusing on utilization of different characteristics and classified as two AMC types [5]. First type of AMCs isfocused on statistical modelsfor estimating the received signal and probability functions.However, this approach has poor performance because of the inaccuracy that happens due to time varying nature of different channel models in the real-world scenario.Furthermore, the complexity of this AMCmethods becomes quite intricate, and number of calculations arealso high, when multiple modulation types are taken into account[6]. The second type of AMC makes use of a machine-learning approach to accomplish the various real-worldgoals. This AMC approach makes use of training data by using support vector machine (SVM)[7], k- nearest neighborhood, random forest, naive bayes methods, which may be used to categories modulation type in various ways. TheSVM technique outperforms among the various machine learning classifiers, when the training data is comparable to the real data, but it may still get decent results even when the computing cost is smaller. But the machine learning algorithms are failed to provide the maximum classification accuracy and the complexity of these methods are increasing as the modulation features are increased. Further, the machine learning classifiers are suffering with the speed related issues during training and testing process.

In order to improve the AMC, different strategies have been investigated, including recurrent neural networks (RNNs) [8], convolutional neural networks (CNNs) [9], and deep neural networks (DNNs) [10]. These deep learning-based models are mainly focused on feature extraction and classification stages. The CNN models were improving the performance computer aided systems in various applications [11] including image processing, signal processing, signal analysis, data processing and video processing. The CNN modelsconvertinput (audio, video, text, and signal) data into feature vectors and analyzes the relationship between various features. This property of CNN is effectively used to classify the signals based on their unique features. Further, the RNN models [12] also extracts the features from these data and additionally they were used for time-series data.But RNN is computationally difficult and needs a significant amount of calculating work in comparison to its performance. In addition, DNNs are used to extract the features from complex conjugated data of inputs and has shown excellent performance for a variety of applications.Recently, DLCNN[13]are developed by combining the properties of CNN, DNN and RNN, which overcomes the problems of individual models. Further, DLCNN models are used to extract the wavelet coefficient, phase dispersion, frequency, and amplitudes from the modulation's schemes.

Multiple studies have concentrated on machine-learning approaches rather than examining the properties of data provided as input in order to get the desired results. Consequently, this work employs DLCNN model for feature extraction, those features that have a significant improvement on classification performance, thereby reducing the computational complexity and increasing the speed with which the received signal is identified while employing the fundamental DLCNN algorithm. These models improvise the importance of each feature map as compared to DNN, RNN. Further, the correlation coefficient is used to select the best features from the extracted data.This correlation coefficient is selecting the features based on mutual signal properties of various modulation schemes.In order to obtain trustworthy, resilient, and efficient AMC performance under various fading channels, every stage of AMC should be implemented by using artificial intelligence based deep learning models. The research area of AMC should be improvised by using deep learning models. As of now there is no controlled, inclusive and comprehensivespecific dataset for AMC process. The existing datasets are failed to considerthe multipath fading effects in various time, frequency varying channels.Thus, this work considered a new publicly available HisarMod2019.1 dataset. Further, this dataset is developed by considering Nakagami–m (m = 2), Rician (k = 3), Rayleigh, static and ideal channel conditions with multiple number of taps.The major contributions of this work are as follows:

- Initially,a novel DLCNN model is developed for extracting the AMC features, which has the potential capacity to improve the classification performance by analyzing the diverse features.
- Further,HELM-B classifier is developed for classifying modulation types, or kinds, as opposed to their individual characteristics, which reduces the computational complexity and improves the accuracy of the system.
- Simulation results shows that the performance of proposed method is improved as compared to the state of art approaches.

Rest of the article is organized as follows: Section 2 delas with the related work with their problems. Section 3 delas with the detailed analysis of proposed method. Section 4 delas with the results and discussions. Section 5 concludes the article.

2. Related Work

This section delas with the literature survey that goes through the conventional methods of obtaining information. Machine learning, deep learning approaches are utilized for AMC classification, although expert knowledge is required for deep learning classification of RF signals. Basic AMC approaches are developed by utilizing the machine learning classifiers with standard feature extractors. In [14] authors developed the cooperative AMC system with by using CNN models, which is specifically designed for the multi-input multi output (MIMO) modules.But this system is failed to classify the time domain modulation schemes. Thus, pruning technology [15] is developed for improving the CNN performance by using the statistical moments-based features. Butthis method is applicable to only edge computing devices but this method is not applicable to MIMO devices. Further, spectral correlation-based methods are used to extract the deep AMC features by using Born-Jordan distribution and smooth pseudo-wigner-ville distributionmodules.Here, Born-Jordan distribution extracts the time sample-based features and smoothed pseudo-Wigner-Ville distribution extracts the frequency bands-based features.

Previous to the advent of machine learning, most signal classification approaches needed extensive domain knowledge as well as the capacity to extract features from recognized signals in order to be classified.Further, Fusion based CNN methods are presented in [17]. This method fused the different features by using deep learning models. However, that careful attention must be given to the preprocessing procedures even after all of this has been done. Further, DLCNN [18] models are used to classify the AMC system.This is exactly why the AMC's work has emphasized time-domain representations throughout its history. To describe a radio frequency signal in the time domain, many people choose to use IQ values.In addition, Lightweight AMC (LightAMC) [19] was developed by using compressive sensing-based feature extraction and deep learning classification.In order to get an amplitude-phase representation, it is common to transform the IQ values to polar coordinates, which is another prominent time-domain format. But this method is applicable to only frequency-based modulation classifications.

Later on, researches are focused on implementationhybrid AMC systems by considering both time and frequency-based modulation families.In [20] authors focused on hybrid implantation of hybrid feature extractors with time domain and frequency domain properties. Then the features were trained and tested with the SVM classification. This method suffers with low classification performance with higher complexity.In [21] authors developed the deep learning-based AMC system by using long short-term memory (LSTM) modules. This system is used to classify the various wireless signals and modulation types for low-cost spectrum sensors. But this method is failed to provide maximum classification accuracy for higher SNR values. Further, time varying nature of the channels also effecting the performance of this systems. Thus, Convolutional Long- Short Term Deep Neural Network (CLDNN) [22] model is developed to overcome the problems presented in LSTM based AMC systems. The CLDNN is a hybrid model, which is developed by combining the CNN, LSTM, and DNNs.The CLDNN model optimizes the losses generated in the LSTM-based AMC and improves the classification performance. Thetraining speed of CLDNN model is improved 2 to 5 % as compared to conventional approaches. But, the CLDNN models are resulting in the poor performance in signal analysis applications.

Transfer learning models are efficient and capable of extracting the deep features as compared to deep learning models. Residual Network (ResNet) is one of the prominent transfer learning models. The ResNet based AMC [23] analyzed the features of various modulation types by using probability analysis and resulted in better performance. Furthermore, an effective feature selection algorithm is introduced in [24] to further improve the performance of ResNet. They used CNN model for feature extraction, RNN model for representative value extraction and the correlation coefficient is used to select the best feature and representative values. Finally, DNN is used to classify the various classes of modulation.But this method is suffering with the high computational complexity and low speed. Thus, Robust CNN [25]based AMC is improved the performance as compared to conventional models. This method developed hybrid CNN model by considering the noise layer, IQ-Matrix layers. These layers are specialized layers and improved the training, testing speed.

3. Proposed Methodology

The demand for increased data rates in real-time mobile, satellite, and military communications necessitates improvements in spectrum efficiency, energy efficiency and error rates, as well as challenges with synchronization. All of these needs were readily met by picking the most suitable modulation scheme for the situation. Furthermore, the carrier frequencies, offset values, SNRlevels, transmission rate, and bandwidths under various channel circumstances are all taken into consideration when selecting the modulation style. Consequently, manual modulation selection techniqueshave failed to pick all of these parameters at the same time and have also failed to improve the transmission efficiency in their attempts at selection. Consequently, AMC is critical in this process, and AMC is utilized to appropriately categories modulation types in order to get the greatest outcomes possible. In most commercial systems, the receiver may provide acknowledgment signals indicating that the modulation scheme of the signal being sent has been recognized by the transmitter. The typical AMC systems make use of the received signal for the purpose of categorization. However, it is hard to accurately forecast the communication properties of receivers used in military applications because of the nature of the technology. Furthermore, jammers have an impact on the signals that are received in military communications systems. Thus, this work implemented deep learning-based AMC system.

Figure 1 shows the block diagram of proposed approach for AMC, which contains DLCNN based feature extraction and HEL-B based classification. Initially, the system is trained with the HisarMod2019.1 dataset. Here, the DLCNN is used to extract the features from quadrature amplitude modulation (QAM), phase shift keying (PSK), pulse amplitude modulation (PAM), and frequency shift keying (FSK) based modulation schemes. The DLCNN has the capability to identity interdependent relationship of various modulations schemes by analyzing each feature of RF signal. Furthermore, DLCNN is used to extract the features from both analog and digital modulation signals under multipath and varying channel conditions. In addition, DLCNN is also maintain the time, frequency, amplitude and phase synchronization of modulation signals during the feature extraction process. Then, the extracted features are applied to HELM-B classifier. Usually, the standard deep learning models are suffering with high computational complexity for achieving the higher accuracy. The ELM models are developed to improve the performance speed, reduced the training time, computational complexity as compared to the traditional models. Thus, the proposed HELM-B classifier resulted in the superior performance and classifies the various modulation types.

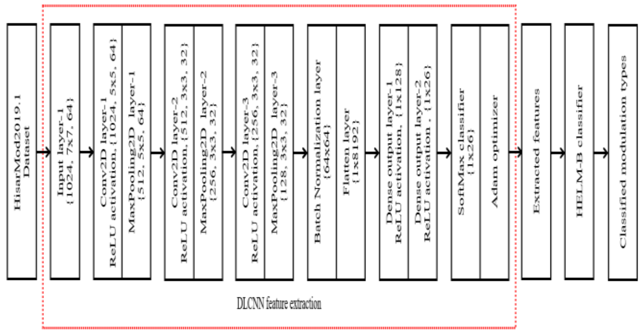

Figure 1: Block diagram of proposed AMC approach using HELM-B classifier.

3.1 Features extraction using DLCNN

Recently, deep learning models resulting in superior performance in many constraint-related problems. This work utilized the DLCNN for extracting the features of multiple modulations schemes with low complexity.In this case, the DLCNN is used to extract features from QAM, PSK, PAM, and FSK modulation families. In order to identify interdependent relationships between these modulation schemes, the DLCNN must first analyses each aspect of the RF signal in order to do so. Furthermore, DLCNN is used to extract features from both analogue and digital modulation signals when the signals are subjected to multipath and variable channel circumstances, among other things. Additionally, throughout the feature extraction process, DLCNN is responsible for maintaining the time, frequency, amplitude, and phase synchronization of modulation signals.Figure 2 presents the detailed feature extraction architecture of DLCNN, and Table 1 presents the layer size related details of each DLCNN model. Table 2 presents the detailed feature extraction algorithmby using DLCNN model.The proposed DLCNN model contains the one input layer, three convolutional layers (Conv2D), three MaxPooling (MaxPool2D) layers, one batch normalization layer, one flatten layer, two dense output layers and SoftMax classifier. Furthermore, these layers are controlled by rectified linear unit (ReLU) activation function and the complexity of the network is reduced by Adam optimizer. The operation of each layer is described as follows:

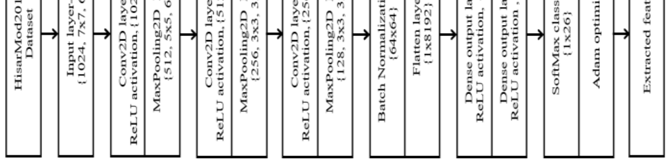

Figure 2. Proposed DLCNN model for feature extraction.

Input layer: This layer is responsible for converting the digital signal data into the feature maps.The input features are produced based on random weight mapping according to any continuous distribution function, and output weights are calculated analytically by the minimal norm solution of a linear system. Here, for each epoch noise will be added, which is used to measure the performance of system for various values of SNR.

Conv2D Layer: This layer is mainly responsible for extracting the feature maps based on interdependent modulation relationships. Consider input of this layer is denoted as x_{in}, which generates the outcome as $x_{out}$with NxD matrix. Here, $N$is the total number of samples in input with dimension D. Further, this layer implements the stochastic probability-based weight function (W). The convolution operation is performed between W and x_{in}, which generated the interconnected features. Finally, conditionaldistribution based bias function (b) is used to classify the features.Equation 1 represents the operation carried out by using Conv2D layer.

$$x_{out} = \max(0, W * x_{in} + b) \tag{1}$$

ReLU: The extracted features of convolutional layer are applied to ReLU activation, which selects the features based on the conditional reliability. The ReLU activation resulted is a piecewise linear function, which maintains the relationship between output to input. The ReLU activation function overcomes the vanishing gradient problem and improves the training speed as compared to sigmoid, hyperbolic tangent activation functions.

MaxPool2D layer: This layer is used to gather the detailed features from previous layers. This layer contains a hidden matrix (H), which performs universal approximation operation by using nonlinear piecewise continuous function($G(\cdot)$). The performance of this layer is superior as compared to average pooling layer, which does not eliminate (reduce) the features.

Table 1. Layer details of DLCNN architecture.

Layer name	Layer dimension	Filter size	No. of filters
Input layer	1024 x 1024	7x7	64
Conv2D-1	1024 x 1024	5x5	64
MaxPooling2D-1	512 x 512	5x5	64
Conv2D-2	512 x 512	3x3	32
MaxPooling2D-2	256 x 256	3x3	32
Conv2D-3	256 x 256	3x3	32
MaxPooling2D-3	128x128	3x3	32
Batch Normalization	64x64	-	-
Flatten	1x8192	-	-
Dense-1	1x128	-	-
Dense-2	1x26	-	-
SoftMax	1x26	-	-

Table 2 DLCNN based feature extraction algorithm.

Input: HisarMod2019.1 dataset.
Output: Modulation type specific features.

Step 1: Apply the dataset to input layer, which converts the dataset values into basic features for multiple SNR values.
Step 2: Convolution layer is used to generate the inter dependent modulation specific features as mentioned in Equation 1.
Step 3: MaxPooling layer is used to grab the maximum individual (subtypes) modulation related features.
Step 4: To improve the efficiency, two sets of convolutions and MaxPoolinglayers are used.
Step 5: Batch Normalization layer is used to reduce the imbalances in the resultant features.
Step 6: Flatten layer is used to generate the feature maps in an array format.
Step 7: Dense layers are used to interconnect the various feature maps (neurons) and generates the robust features.
Step 8: Adam optimizer is used to reduce the losses in the overall deep learning model.
Step 9: Finally, SoftMax classifier is used to generate the modulation specific features as mentioned in Eq. (2).

Batch Normalization layer: Using batch normalization, a transformation is applied that keeps the mean output near to 0 and the standard deviation output close to 1 while maintaining the variance output close to 1. It is important to note that batch normalization behaves in a distinct way during training and inference. In the context of training extremely deep neural networks, this is a method that standardizes the inputs to a layer for each mini batch of data. Consequently, the learning process becomes more stable, resulting in a significant reduction in the number of training epochs necessary for deep networks to be trained.

Flatten Layer: The flatten layer has been used to transform a multidimensional input into a one-dimensional input. It is often utilized in the transition from the Conv2D layer to the fully connected layer. A flatten layer reduces the spatial dimensions of the input to the channel dimensions by using a flatten layer.

Dense Layer: This layer is used to connect (map) the numerous neurons and generates the generalized outcome. The reliabilities of the data changed continuously, so these dense connections are useful for making the constant unchanged output.

SoftMax Classifier: This layer is used to classify the nature of modulation type and generated the modulation specific features. Here, the classification process is used to identify the interdependency of each modulation type feature map with other features. Further, features of each modulation type are grouped together and formed as the trained features. Equation 2 represents the classification process.

$$S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_i}}, \qquad i, j = 1,2, \ldots\ldots, N \tag{2}$$

where $S(y_i)$ represents features, y_i represents dense layer output and N number of modulation classes, respectively.

Adam optimization: Usually DLCNN models are suffering with losses due to multiple number of layers for each epoch. These losses can cause to reduction of overall performance of the systems. Thus, the Adam optimization is used to reduce the losses by analyzing the complexity of modulation specific signals. This model updated the weights of each layer and resulted in better performance as compared to stochastic gradient process. Finally, loss optimized modulation specific features are generated.

3.2 HELM-B Classification

In machine learning, bootstrap aggregation (also known as bagging) is an ensemble approach that is utilized to improveaccuracy and stability of algorithm by reducing classification problem. The bagging is used to divide the main training dataset into sub-datasets. During this division process sampling and replacing of datasets is used. Then different types of classifiers are used to train the data and predict the outcome based on the average of all tested samples.The conventional ELM is regarded as the "base learner" for the bagging technique because of its simplicity.But the ELM is failed to identify the week learners in sub training datasets and unable to improve the accuracy of week learners. Further, conventional ELM is failed to predict the best predicted class, this is due to the fact that bagging helps to reduce the unpredictability of forecasts. Thus, the ultimate choice in a classification model that employs bagging is reached via the use of a majority voting system.

Incorporating the bagging ensemble model into the HELM is primarily intended to increase the classification accuracy and stability. The suggested HELM-B classifier's structure is shown in Figure 3. The operation of HELM-B is illustrated as follows:

1. Bagging module of HELM-B divides the dataset into k groups of various training data subsets.
2. Train kHELM classifiers using appropriate training data subsets, and then acquire k trained HELM features as a result of the training process. These HELMs are functioned in a parallel fashion.
3. Identify the week learners during the training process and improved the performance of week learners by changing the dataset applied.
4. Calculate the predicted modulation class label for the test data set based on the k trained HELM classifier, and HELM-B generates k prediction results from the test features.
5. Finally, HELM-B applies majority voting operation on the individual HELM classification results, which generates the final modulation type classification.

The deep learning structure of HELM is represented in Figure 4, which contains N number of hidden nodes, N number of input nodes, and m number of output nodes, and it is divided into three sub-layers. Consider the input features extracted from DLCNN as $x = (x_1, x_2, \dots, x_N)^T$ and it is applied to input layer. A set of weights w_i=$[w_{i1}, w_{i2}, \dots, w_{iN}]^T$is used to link all of the nodes of the input layer with nodes of hidden layers, where N is the number of weights.Further, bias weights B_j =$(B_{j1}, B_{j2}, \dots, B_{jN})^T$ are used to interconnect nodes of hidden layer with nodes of output layer. The hidden layer performs the operation using hidden matrix H and it is mentioned as follows:

$$H = g\left(w_i^T x + b_i\right) \quad (3)$$

Here, $g(.)$ denotes the activation function of HELM, b_i is the bias function of HELM.

Finally, the convolution operation is performed between B_j and H, which generates the predicted vector $\bar{y} = (\bar{y}_1, \bar{y}_{2,} \dots, \bar{y}_m)^T$ and it is given as follows:

$$\bar{y} = \sum_{j=1}^{\bar{N}} B_j * H \quad (4)$$

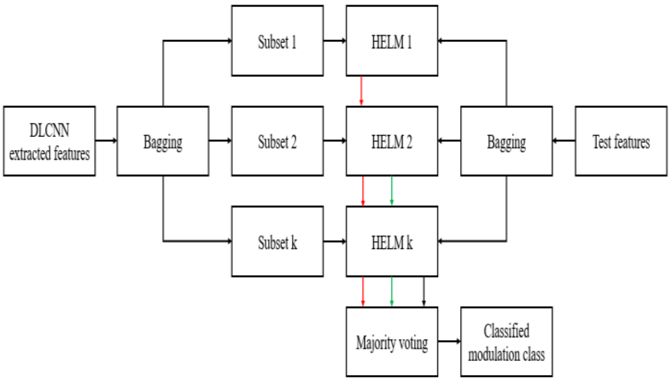

Figure 3. Block level structure of HELM-B classifier.

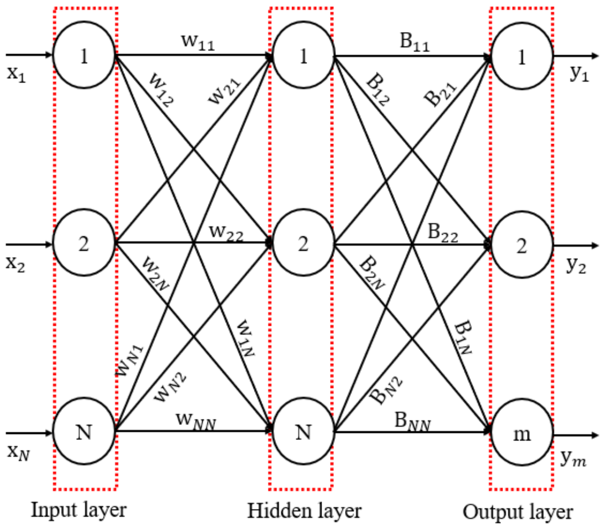

Figure 4. Deep learning structure of each HELM.

The conventional ELM selects the B_j and w_i are generated randomly from a pool of possible values, which are not generated by static training process. But, this resulted in the reduced performance, thus this work modified this property of ELM and formed as HELM, which generates the B_j and $w_i$weights from novel training set (s) by using reinforcement learning.

$$s = [(x_k, y_k)|x_k \in R^k, y_k \in R^m, \text{k} = [1, 2, ..., \text{K}]] \quad (5)$$

Here, $y_k = [y_{k1}, y_{k2}, \dots, y_{kk}]$ and $x_k = [x_{k1}, x_{k2}, \dots, x_{kk}]$ is the output and input vectors k^{th} training instance. Further, B_j and $w_i$weights are generated by optimizing the training set. Equation 6 represents the objective function of optimization process, which needs to solved and minimized for efficient outcome.

$$L(B, \zeta) \;=\; \frac{1}{2}\left\|B^2\right\| + \frac{c}{2}\sum_{k=1}^{k}\left\|\zeta_k^2\right\| \quad (6)$$

$$H(w_k) = L(yk - \zeta_k) \quad (7)$$

Here, $L()$ represents the feedback process, C represents the regularization parameter, ζ_k represents the predicted error of instance $k, h(w_k)$represents the hyperparameter of w_i and it is feedback to hidden layer from output layer.E

$$H(w_k) = \begin{bmatrix} g(w_1^T x_k + b_1) \\ g(w_2^T x_k + b_2) \\ . \\ . \\ g\left(w_N^T x_k + b_N\right) \end{bmatrix} \quad (8)$$

For the purpose of solving the optimization constraint stated above, apply the Kuhn–Tucker conditions such as Lagrange multipliers, and the resulting solution is generated follows:

$$\vartheta_{Bw} = \left(\frac{I_{\bar{N}\times\bar{N}}}{C} + \left(H(w_k)\right)^T H(w_k)\right)^{-1} \left(H(w_k)\right)^T \Upsilon \quad (9)$$

Here,ϑ_{Bw} is the optimized value of B_j and w_i weights, $I_{\bar{N}\times\bar{N}}$represents an identity matrix and Υrepresents output feedback constant. Finally, the layers of HELM updated with optimized ϑ_{Bw} weights and generates the output vector y_k.

$$y_k = \begin{cases} class\ A: & \rho^{class\ A} > \rho^{class\ B} \\ class\ B: & \text{else} \end{cases} \quad (10)$$

Here, $classA$ to $classB$represents 26 classes of modulation types with 5 major modulation types.Here, $\rho^{class\ A}$represents probability of $class\ A$ modulation type and $\rho^{class\ B}$ represents probability of $class\ B$ modulation type.Now, this is HELM is applied to bagging classifier and Table 3 presents the algorithm of HELM-B. The process of HELM-B is divided into training and testing phases. The features generated from HisarMod2019.1 dataset are divided into 80% for training and 20% for testing. During the training process optimized B_j and w_i weights for each HELM classifier is calculated and they are applied as input to the HELM-B testing model.

Table 3. HELM-B classification algorithm

Input: Trained features: s, Test feature:ψ_{test}
Output: Predicted modulation class of the test data sequence

Step 1: Apply the DLCNN trained features (s) to bagging classifier of HELM-B.
Step 2: Initialize the bagging process and divide the dataset into multiple sub dataset.
Step 3: Perform the HELM classification operation on each sub dataset.
Training Phase
Step 4: Generate the optimized value of B_j and w_i weightsfrom the training process.
Step 5: Identify the week learners of HELM-B classifier and optimize the week learners with updated dataset.
Step 6: Finalize the hidden matrix of hidden layer, output layer by using optimal weights.
Testing phase:
Step 7: Apply the test features (ψ_{test}) to bagging classifier of HELM-B.
Step 8: Apply the optimized B_j and w_i weights to testing model of HELM-B.
Step 9: Improve the performance of each week learners by updating the weights in feedback manner.
Step 10: Further, majority voting operation is performed between probabilities of sub datasets classification performance for final decision.
Step 11: Finally, modulation classes are classified using equation 10.

4. Results and Discussion

This section gives the detailed result analysis of proposed method in comparison with the various state of art approaches.The state of art approaches and proposed method considered the same datasets.

4.1. HisarMod2019.1 dataset

The HisarMod2019.1 dataset[26] contains 26 modulation types from 5 distinct modulation families as shown in Table 4. Further, the datasetcontains analogue, QAM, PSK, PAM, and FSK modulation signals, which are considered under multipitch fading environment.For each modulation type, there are 1500 signals in the dataset, each with a length of 1024 I/Q samples and a length of 1500 I/Q samples. HesarMod2019.1 has been designed to be comparable to RadioML2016.10a in order to provide a fair comparison. There are 20 distinct signal–to–noise ratio (SNR) levels available between -20dB and 18dB. As a consequence, there are 780000 signals in total covered by the dataset. For the purpose of producing signals, the oversampling rate is set to 2 and a raised cosine pulse shaping filter with a roll–off factor of 0.35 is used. Furthermore, the dataset contains signals flowing via 5 distinct wireless communication channels, including Nakagami–m (m = 2), Rician (k = 3), Rayleigh, static and ideal.There are 300 signals for each modulation classes in the dataset because these channels are equally likely to be scattered across the datasetfor each SNR level. The term "ideal channel" refers to the absence of fading and the presence of additive white Gaussian noise (AWGN). Further, the static channel coefficients are set at the start of the propagation period by chance and stay constant throughout the propagation duration. By using signals that flow over the Rayleigh channel, it is possible for the system to be resistant to non–line–of–sight circumstances. The effects of the AWGN channel are induced to noise, interferences presented in the received signal, which degrades the AMC performance. So, the proposed method effectively extracts the noise dependent modulation features to overcome this problem.Due to the fact that the dataset contains only modest fading, Rician fading with a shape parameter, k, of 3 is used on the other hand. Apart from these channel models, the Nakagami–m distribution of received power with a shape parameter of 2 is chosen for the remainder of the signals in the dataset, with m being the shape parameter. As a consequence, the collection contains signals with a variety of fading characteristics. It should be noted that the number of multipath channel taps will almost certainly be either 4 or 6, as specified in ITU–R M1225.

Table 4. List of 26 modulation classes of 5 modulation families.

Modulation family	Analog	FSK	PAM	PSK	QAM
Modulation classes	AM–DSB AM–SC AM–USB AM–LSB FM PM	2–FSK 4–FSK 8–FSK 16–FSK	4–PAM 8–PAM 16–PAM	BPSK QPSK 8–PSK 16–PSK 32–PSK 64–PSK	4–QAM 8–QAM 16–QAM 32–QAM 64–QAM 128–QAM 256–QAM

4.2. Classification results

Figure 5 presents the confusion matrices of various modulation classification methods including LSTM [21], CLDNN [22], Robust-CNN [25] and Proposed approach. From figure 6, it is observed that the proposed approach contains the higher true positive values and lower true negative values as compared to the conventional approaches, which significantly improves the accuracy for each modulation types. The difference between various levels is used to classify each modulation type easily.

Table 5 presents the detailed performance of various modulations schemes with respect to multiple performance metrics. From the comparison, it is observed that the QAM method resulted in better accuracy, precision, recall and F1-score as compared to other modulation schemes. Even though, the other modulations schemes also achieved prominent classification results.

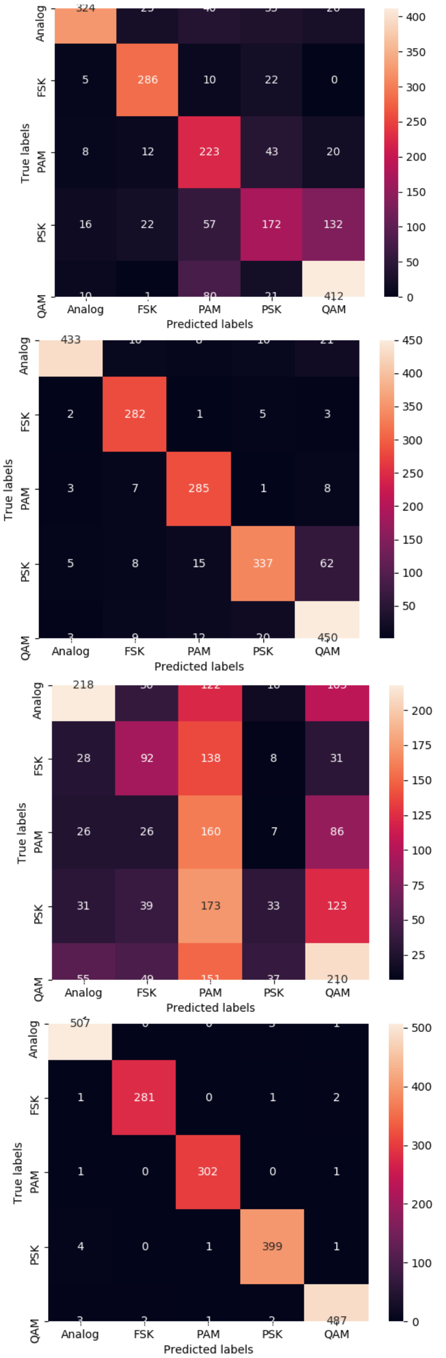

Figure 5. Confusion matrices of various modulation classification methods. (a)LSTM [21]. (b) CLDNN [22]. (c) robust-CNN [25]. (d) proposed HELM-B classifier.

Table 5.Performance estimation of variousmodulationtypes using proposed HELM-B classifier.

Modulation type	Accuracy (%)	Precision (%)	Recall (%)	F1-score
Analog	94.276	97.001	96.701	96.907
FSK	95.012	97.156	96.729	97.324
PAM	97.991	97.569	96.866	98.988
PSK	98.479	99.159	98.750	99.469
QAM	99.820	99.972	99.101	99.545

Table 6. Performance comparison of existing and proposed AMC using HELM-B classifier.

AMC method	Accuracy (%)	Precision (%)	Recall (%)	F1-score
SVM [20]	54.728	57.847	77.032	63.694
LSTM [21]	62.470	61.283	60.954	63.572
CLDNN [22]	87.761	75.030	75.449	75.217
ResNet [23]	81.402	82.667	81.525	82.078
Robust-CNN [25]	92.868	92.160	96.764	95.765
Proposed HELM-B classifier	99.158	98.936	97.262	98.735

Table 6 compares the performance of proposed HELM-B classifier-based AMC systems with conventional AMC methods such as SVM [20], CLDNN [22], ResNet [23] and Robust-CNN [25]. The works SVM [20] is basic machine learning approach and CLDNN [22], ResNet [23] and Robust-CNN [25] are standard deep learning approaches. The comparison results show that, the proposed method gives the superior performance in accurate modulation classification process as compared to the state of art approaches. Further, Figure 6 illustrates the performance metrics obtained for various modulation families using proposed HELM-B classifier, whereas Figure 7 demonstrate the performance comparison of obtained quality metrics using existing and proposed AMC models.

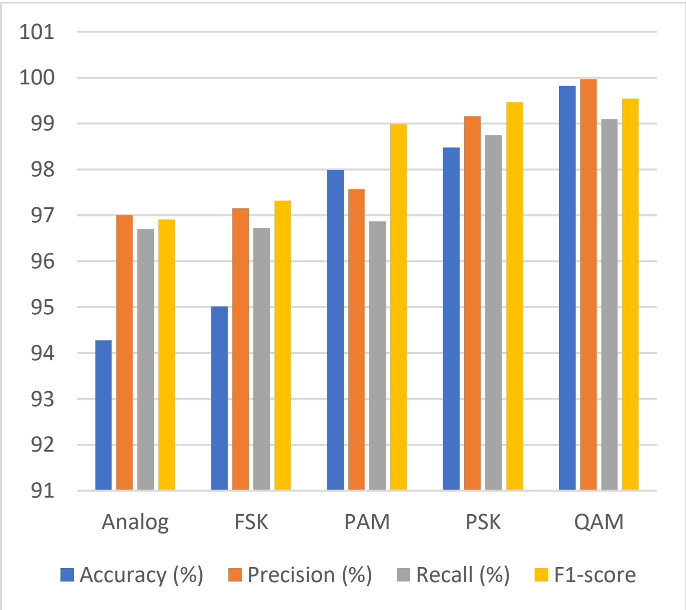

Figure 6. Comparison of quality metrics obtained for different modulation family using proposed HELM-B classifier.

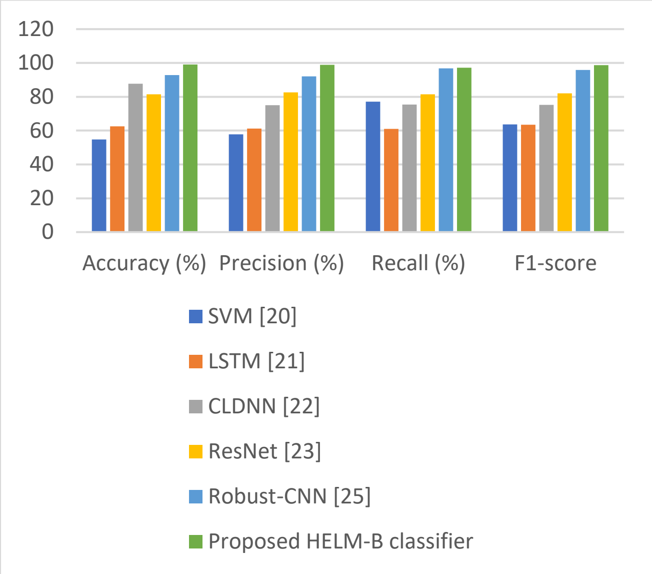

Figure 7. Performance comparison of obtained quality metrics using existing and proposed AMC models.

5. Conclusion

This work focused on implementation of deep learning-based AMC by using DLCNN feature extraction and HELM-B classification.The DLCNN was able to extract the modulation specific and inter dependent modulationfeatures from the HisarMod2019.1 dataset. The HELM-B was developed by using the hybrid version of ELM and bagging classifiers, where the problems presented in the conventional ELM is overcome by optimizing the weights.The performance of HELM-B is improved by dividing the dataset in subsets, which also reduced the training complexities. Further, the proposed method accurately classified the various modulation types, which meets all the spectrum requirements in a multipath fading scenario.The results of the simulation reveal that the suggested AMC system outperforms the performance of traditional AMC systems in terms of overall performance.Thus, the results proved that the proposed AMC is suitablefordifferent communication systems, such as commercial, telecommunication, and military applications.Further, this work can be extended with optimal feature selection basedDLCNN approaches, which can enhance classification accuracy.

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