Automatic Modulation Classification Using Deep Learning Techniques

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***Abstract*—Automatic Modulation classification is a technique utilized to blindly classify the modulation scheme of a received complex signal. Three feature based approaches were studied and evaluated. For the first, approach, a CNN+GRU model is created such that the CNN layers extract relevant features from the received vector, and GRU layers extract features relating to the temporal nature of modulation schemes. The second approach utilized handcrafted features which are the HOCs of the received vector. certain HOCs are calculated and used as features for classification. Lastly, the third approach addresses the problem as an image classification problem by extracting the joint recurrent plots from the received complex vector. The proposed approaches will be tested using the RadioML2018.01A dataset which contains 24 different modulation schemes with SNRs varying from 30dB to -20dB. The results indicate that the proposed CNN+GRU model can perform relatively well at high SNRs, and that the use of HOCs promises relativity good classification accuracy at lower SNRs for simple modulation schemes.**

***Index Terms*—Automatic Modulation Classification, CNN, deep learning, feature extraction, HOCs, GRUs, Hierarchical classification,Recurrent Plot**

I. Introduction

Automatic Modulation Classification (AMC) is the process of blindly classifying a transmitted modulation scheme that has been corrupted by noise and the effects of the communication channel without any prior information regarding to the modulation type. AMC has major applications in both military and civil applications[1]. For instance, AMC can be utilized for electronic warfare to intercept enemy communication channels and potentially decode the information being exchanged. In addition, AMC can be used for dynamic spectrum access, and for spectrum monitoring applications. However, the propagation channel characteristics, noise, and interference interact together to change the transmitted waveform in unpredictable manners. Hence, classifying between different modulation schemes becomes extremely tough.

There are two main categories to AMC, the likelihood based approaches and the feature based approaches[2]. In the likelihood based classification schemes, the likelihood function for the received complex signal is calculated for each different modulation scheme[3]. The correct modulation scheme is chosen based on the maximum likelihood function. However, likelihood based classifiers require knowledge of channel state information (CSI) to account for the communication channel characteristics [4]. On the other hand, feature based techniques extract relevant features from the received complex signals and classify the modulation scheme based on any specified decision algorithm. Further, feature based schemes are less complex and require less computations compared to likelihood based schemes[2]. In addition, machine learning techniques can be employed to perform both the classification task, and the feature extraction task.

II. Related Works

A. Higher Order Cumulants approach

A feature based approach studied in [2] utilized handcrafted statistical features from the complex received signal. Different normalized Higher Order Cumulants (HOCs) of the received signals were calculated, and the magnitudes of these HOCs were utilized as the classification features. This was done because HOCs can mitigate the effects of AWGN as the HOCs of a normally distributed random process, such as AWGN, is essentially zero [5]. The different HOCs utilized are summarized in Fig.1.

HOCs		HOMs Expression
Second Order Cumulants	C_{20}	M_{20}
	C_{21}	M_{21}
Fourth Order Cumulants	C_{40}	$M_{40} - 3M_{20}^2$
	C_{41}	$M_{40} - 3M_{20}M_{21}$
	C_{42}	$M_{42} - \lvert M_{20}\rvert^2 - 2M_{21}^2$
Sixth Order Cumulants	C_{60}	$M_{60} - 15M_{20}M_{40} + 30M_{20}^3$
	C_{61}	$M_{61} - 5M_{21}M_{40} - 10M_{20}M_{41} + 30M_{20}^2M_{21}$
	C_{62}	$M_{62} - 6M_{20}M_{42} - 8M_{21}M_{41} - M_{22}M_{40} + 6M_{20}^2M_{22} + 24M_{21}^2M_{20}$
	C_{63}	$M_{63} - 9M_{21}M_{42} + 12M_{21}^3 - 3M_{20}M_{43} - 3M_{22}M_{41} + 18M_{20}M_{21}M_{22}$

Fig. 1. Classification HOCs [2].

The dimensionality of the feature space was then increased by using polynomial expansion to further separate the different modulation schemes. Further, in [2], the classification problem was approached using a Local Classifier per Parent Node (LCPN) hierarchical classification approach. IN this approach, a multi-class classification problem is divided into multiple binary classification problems. This approach utilizes any apparent hierarchy between the different classes in a multi-class classification problem, and it helps in reducing the complexity of the classification algorithm [2]. The classifier starts by classifying the received signal as either belonging to Quadrature Amplitude Modulation (QAM) schemes or the Phase Shift Keying (PSK) schemes. Further, each parent classifier is followed by a sub-classifier that classified between higher order QAM or PSK modulations and the simplest forms of each family of modulations schemes as seen in Fig.2.

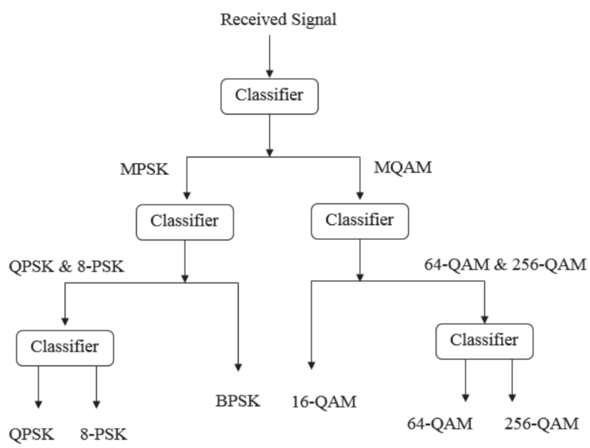

Fig. 2. LCPN hierarchy [2] .

Lastly, [2] reports that the classification accuracy of their proposed method relies on the number of received symbols utilized to calculate the HOCs as a classification accuracy of 97.94% was achieved with 10,000 symbols versus 87.93% with 1000 symbols only at a testing SNR of 10 dB.

B. CNN+LSTM approach

Another approach studied by Xie et al. [6] utilized a densely connected convolutional neural network (CNN) in combination with a bidirectional long-short-term-memory (BLSTM) neural network for classification. The CNN was utilized to automate the process of feature extraction, and the BLSTM was used to take advantage of the temporal nature of the received complex signal. The dataset utilized was the RadioML2016.10a dataset, and the signal-to-noise ratios (SNRs) used to train and test the model varied from -20 dB to 18dB. The results reported by indicate that the model performs well on higher SNRs, but it struggles to differentiate between higher order QAM and PSK modulation schemes as the SNR is lowered as clearly seen in Fig.3.

C. 2-D AlexNet

Zhu et al. [4] reported an approach where a modified ALexNet like structure was used for AMC. The complex channel gain, which adds random phase changes and attenuation's to the receives signal, was taken into account in addition to AWGN to simulate a more realistic classification approach. Before being fed to the classifier, the input signal was normalized first using the mean and standard deviation of the real and imaginary parts of the signals separately. The resulting normalized complex signal was then turned into a constellation image of size 224x224 to match the input size of AlexNet. Further, Zhu et al. [4] approach increases the number of pooling layers in AlexNet to create a model named Accelerated AlexNet (AAN). Zhu et al. [4] reports that AAN

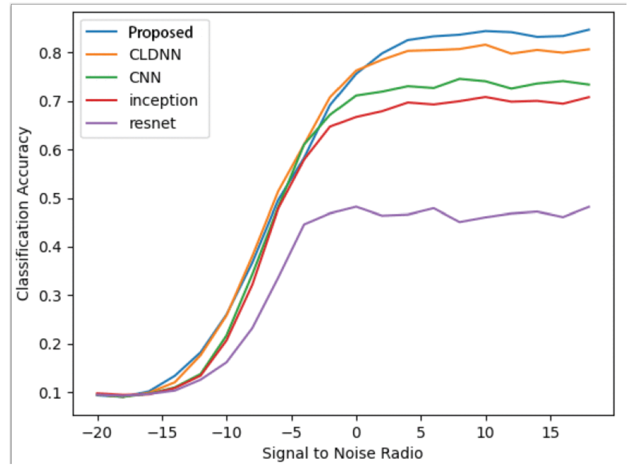

Fig. 3. Classification accuracy vs SNR for different models [6].

converges faster for the AMC task with minimal effects on the classification accuracy. Average pooling was utilized to smooth out the effects of the AWGN on the input images rather than the max pooling layers utilized in AlexNet. In addition, Zhu et al. [4] reports that using the Tanh activation function mitigates the vanishing gradient problem faced when using RELU activation functions which happens as a consequence of premature convergence. Lastly, the ADAM optimizer was utilized instead of the stochastic gradient descent optimizer to utilize the momentum of the weights when performing back propagation. The model was trained to classify between Quadrature Phase shift keying (QPSK), 8-Phase shift keying (8-PSK), 16-QAM, and 64-QAM. The classification accuracy follows the same trend as other models with lower accuracy at lower SNRs, and a high classification accuracy at high SNRs. However,Zhu et al. [4] conclude that with the addition of random phase offsets, the proposed AAN maintains its performances at a fixed SNR unlike other models.

D. Attention Based CNN

Huynh-The et al. [7] propose an efficient CNN architecture which incorporates the attention mechanism to strengthen useful features and discard irrelevant ones. The proposed model was tested using the RadioMl2018.01A. the dataset contains 24 different modulation schemes with varying SNRs from -20 dB to 30 dB in steps of 2 dB. each signal contains 1024 complex samples such that each modulation class contains 106,496 signals with varying SNRs.Huynh-The et al. [7] introduced some further signal degradation by adding Doppler shift, frequency offset, sampling time drift, and Rician Fading to incorporate the effects of an actual communication channel when evaluating the model. The model's performance over different SNR values can be summarized in Fig.4, and it suggests that the proposed model performs better at higher SNRs compared to other proposed models.

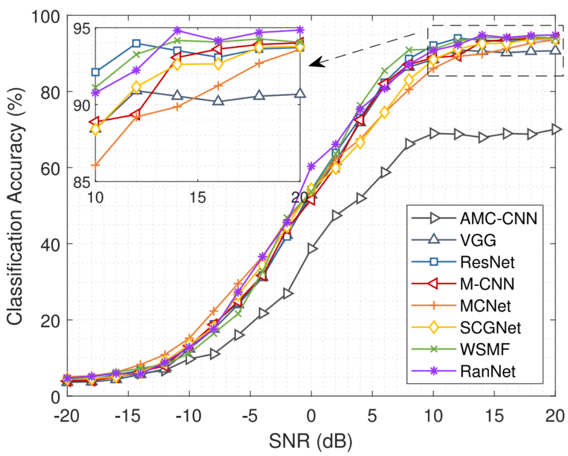

Fig. 4. Classification accuracy vs SNR for different models [7].

E. *An Imaging approach to Time Series Classification*

Bertalanic et al. [8] employed multiple different feature transformations to redefine the time series classification problem into an image classification problem. The first transformation used is the Recurrent Plot (RP) transformation. the RP transformation takes in a 1-D time-series vector and creates a matrix which shows the similarity between different elements in a single time series sequence. Another transform used was the Gramian angular field transformation which represents the temporal correlation between points within a time series. By utilizing both transforms, the time series classification problem can be translated into an image classification problem. Bertalanic et al. [8] report high accuracy and F1 scores reaching 0.99 when employing this approach for wireless anomaly detection.

III. Proposed Approach

For the purpose of this paper, three main approaches will be studied. The first approach will utilize a CNN to automate feature extraction, and a Gated Recurrent Unit (GRU) to extract the temporal information present in modulation schemes. The CNN is a shift invariant neural network that extracts features through filters. The weights of these filters are optimized to minimize the loss function of choice whilst training the CNN. On the other hand, the GRU is a recurrent neural network which incorporates the temporal dependency of an input sequence. This is done by utilizing the outputs of preceding inputs to the GRU layer as additional inputs to the current input. The features utilized for training will be the raw complex signals.

The second approach will utilize the same CNN+GRU with the addition of utilizing handcrafted features. The cumulative HOCs as specified by Abdelmutalab et al. [2] will be used as the input features instead of the raw complex signal. This approach will help in reducing the complexity of the model by reducing the variety and length of the feature sequence of each input. Lastly, the third approach will address AMC as an image classification problem. This will be done by calculating the joint Recurrent Plot of the inputted complex vector and reshaping it into an appropriate size for training. The resulting images will then be used to train a simple CNN model.

The dataset utilized is the RadioML2018.01A which contains 24 different modulation schemes with varying SNRs from -20 dB to 30 dB in steps of 2 dB. the SNRs were limited from -10dB to 30dB to ease feature extraction, and no additional channel impairments were added. The classification task was repeated twice for each of the proposed approaches. For the first classification task, the 24 different modulation schemes were each treated as a separate class, and a multi-class classification approach was employed by utilizing a categorical cross-entropy loss function to update the parameters of the model. As for the second classification task, a similar approach to Abdelmutalab et al. [2] was employed by which a series of binary classifiers were trained to create a LCPN hierarchical classifier to classify the same schemes as specified in Fig.1.

IV. Multi-Class Modulation Classification

A. *CNN+GRU approach*

For the first approach, the SNR range over which the classifier was trained over was varied to view how the classification performance changes as a function of the training dataset's SNR range. Each model's performance was then tested at the different SNRs to view how the model performs as a function of the SNR value. The results in Fig.5 summarize the performance of a simple 1-D CNN architecture used to benchmark the performance of the proposed approach. The results indicate that utilizing a training SNR ranging between 30dB to 10dB provides the best performance compared to the other tested SNR ranges.

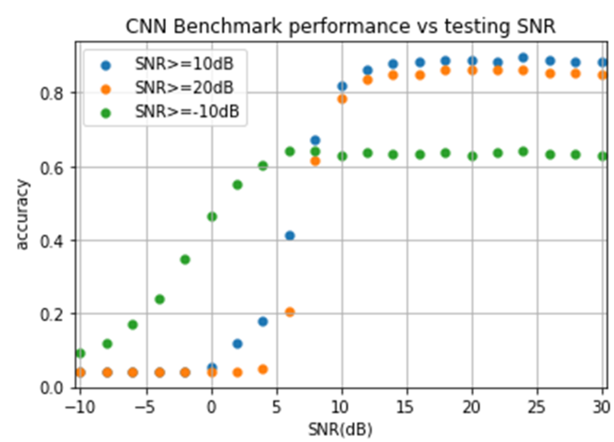

Fig. 5. Classification accuracy vs SNR for different training SNR ranges.

A possible explanation for this is that when the SNR range was limited between 20dB to 10dB, the classifier was learning features that easily get degraded by noise. In contrast, when the classifier was trained on SNR values ranging from 30dB to -10dB, the classifier was struggling to learn relevant noise invariant features that are common between low and high SNR signals due to the high level of signal degradation. This is further observed in Fig.5 as the classifier's performance at lower SNRs degrades extremely when the training SNR range is reduced, and the classifier's performance at higher SNRs degrades if the training SNR range is increased. Consequently, this presents a trade-off between the robustness of the classifier and its actual performance in terms of accuracy.

The proposed CNN+GRU model peforms relatively better than the simple CNN approach. This was expected as the GRU layers introduce the capability of learning temporal features from the inputted features vector. the proposed multi-class CNN+GRU model was trained utilizing SNRS between 30 dB to -10 dB. Fig.6 compares the performance of the proposed model to benchmark CNN model. The results indicate that the model's performance is better at higher SNRs with minimal effects to the model's robustness.

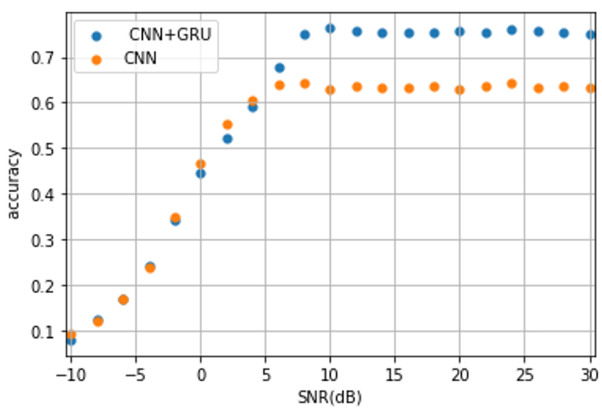

Fig. 6. Classification accuracy vs SNR for Proposed CNN+GRU model trained on SNR¿=-10dB.

B. CNN+GRU using HOCs approach

To simplify the model and reduce the computational complexity of extracting relevant features from the raw complex signal, the normalized cumulative HOCs of the received complex signal vector were calculated. The HOCs as specified in Fig.1 were estimated in a cumulative way such that for each input sequence of length 1024, each 128 IQ samples are grouped together and their respective HOCs were calculated. Hence, the starting input shape of (1024,2) per signal is transformed to (8,9). The model results shown in Fig.7 indicate that the accuracy is low overall in both tested iterations. This was to be expected as the input feature's variation was reduced. Nevertheless, the HOC CNN+GRU model trained with an SNR¿10dB performs relatively better at lower SNRs than the benchmark CNN model.

C. Image Based Modulation Classification

In this approach, the number of classes was limited to 4 classes only, OOK, BPSK, QPSK, and 16-QAM. for each feature vector of size (1024,2) the joint Recurrent Plot wave evaluated and the resulting 1024x1024 matrix was transformed into an image of size 128x128. Fig.8 shows some example RPs at different SNRs.The results shown in Fig.9 indicate that this

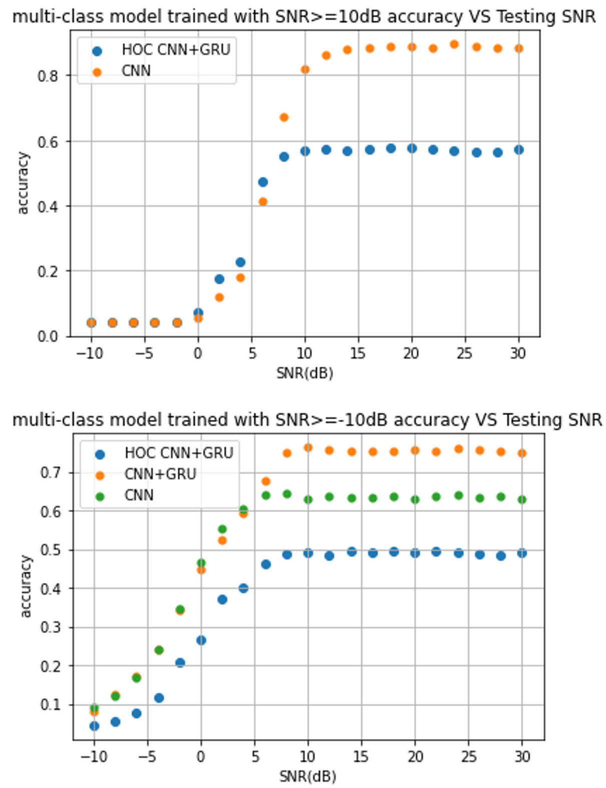

Fig. 7. Classification accuracy vs SNR for HOC CNN+GRU classifier.

proposed methodology does not perform well for AMC as utilizing the similarity between the imaginary and real parts of the complex received vector produces similar images for different modulation schemes. Further, an increase in signal degradation results in highly similar extracted images from different modulation schemes.

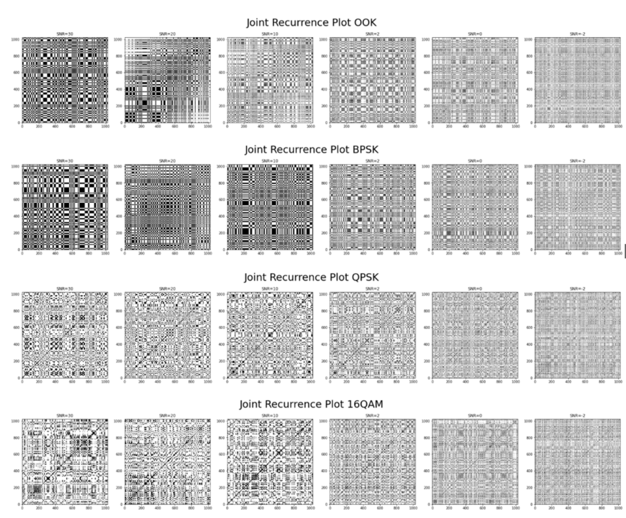

Fig. 8. Joint Recurrent plots.

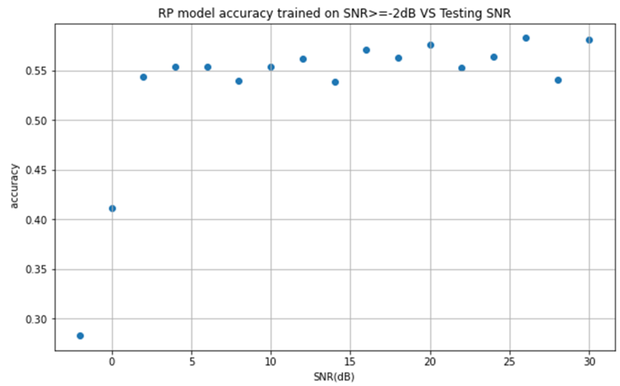

Fig. 9. Classification accuracy vs SNR for RP CNN classifier.

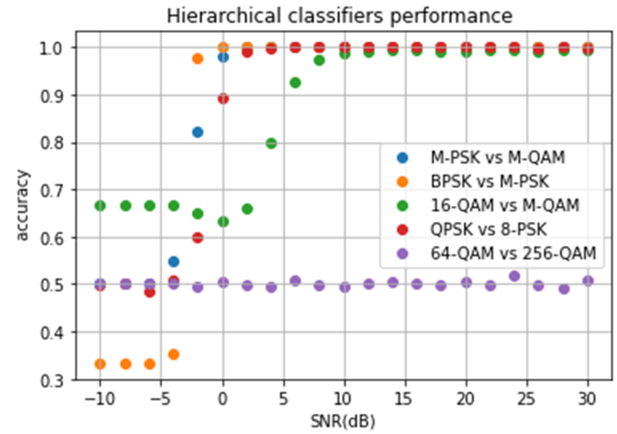

Fig. 10. Hierarchical Binary Classifiers Performance.

V. Hierarchical Modulation Classification

In this section, the same dataset was utilized, but the modulation schemes were limited to 6 classes only which are BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, and 256-QAM. Classifying Modulation schemes is an inherently hierarchical classification task as most digital modulation schemes either belong to the generalized M-PSK, M-QAM, M-ASK, or orthogonal modulation schemes such as M-FSK. Thus, if the classification problem is addressed as a normal multi-class classification task, the members of the specified modulation families would be treated as completely different classes although they mostly have similar structures within each family. This was hinted by the results of the multi-class approach as most missclassifications occurred between similar modulation schemes. Consequently, misclassification between similar modulation schemes is increased as was noticed when performing the first blind approach. Thus, dividing the classification problem in multiple sub-classification problems does not only reduce the computational and model complexity, but it also forces the classifier to learn relevant features that help in differentiating between similar modulation schemes. Thus, the hierarchical approach specified by Abdelmutalab et al. [2] was tested using the proposed deep learning model.

A. CNN+GRU approach

The same methodology discussed in the previous section was utilized with a different CNN+GRU layers configuration. As the classification task was divided into multiple hierarchical binary classifiers, the model's complexity and convergence time were greatly reduced. The performance of the model was then tested using testing subsets with different SNRs. The performance of each binary classifier is reported in Fig.10. However, a more appropriate approach would be to evaluate the performance of the full hierarchical classifier as one model. Hence this can be explored in future work. The results clearly show that the proposed CNN+GRU model struggles to differentiate between higher order QAM constellations. This is expected as with any Square QAM constellation, the degradation of the transmitted signal deteriorates the square constellation which increases the complexity of extracting useful features to differentiate between higher order M-QAM modulation schemes. Hence, a different architecture should be explored to classify between higher order QAM constellations.

B. CNN+GRU using HOCs approach

The same approach as discussed in the previous section was repeated and the results suggest that the HOC approach to binary classification requires more elaborate experimentation. Fig.11 summarizes the results for the parent classifier in the LCPN hierarchical classifier, and the BPSK vs M-PSK classifier. The results clearly suggest that the model was able to extract relevant information about how AWGN degrades the different modulation schemes, and it was able to classify low SNR signal with good accuracy. However, the model's performance at the remaining classifiers deteriorated extremely due the similarity between the AWGN corrupted higher order M-QAM and M-PSK modulation schemes. Consequently, it can be concluded that HOCs can be utilized for low SNR AMC, but further studies can be done to improve the classification process.

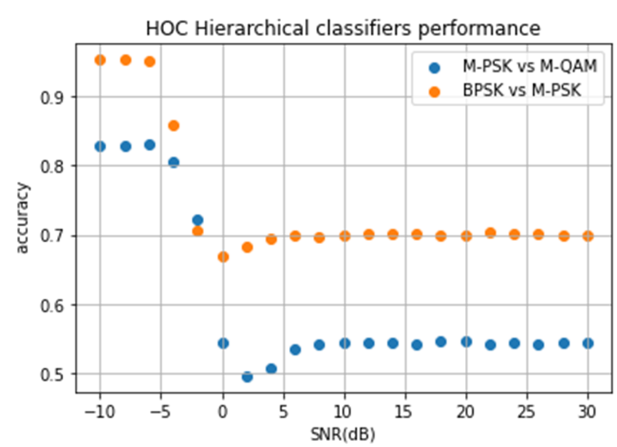

Fig. 11. Hierarchical Binary Classifiers Performance.

VI. Conclusion

Although the proposed CNN+GRU model performs relatively well, it must be noted that no realistic channel impairments caused by Doppler shift, channel fading, co-channel interference, phase offsets, and clock drift were taken into account for the scope of this work. Thus, it is expected that the model's performance will deteriorate if applied in real world scenarios. Further, the experimentation results clearly suggests that addressing AMC as a normal multi class problem reduces the performance of the classifier on similar modulation schemes. Consequently, addressing AMC as a hierarchical classification problem will yield better results. In addition, some of the techniques that can be further explored is the use of generative models such as GANs, VAEs, or denoising diffusion models on top of the classifiers to introduce some form of signal denoising.

Moreover, a more appropriate approach that can be evaluated is to have a hierarchical classifier which utilizes an ensemble of different models for each binary classifier in the hierarchy. To elaborate, if we have a parent classifier that classifies between M-QAM and M-PSK, instead of classifying between these two different classes using a single model, multiple models can be used as an ensemble. Each of the members of the ensemble can be trained on different SNR ranges such that each classifier inside the ensemble is able to extract relevant features at different SNR values. Further, each member of the ensemble can utilize different features from the received complex signal to aid in classification at different SNRs. The classification can then be done using a majority vote technique, or by assigning each model in the ensemble a weight. The same procedure can be repeated for each classifier in the LCPN hierarchical classifier such that a robust AMC model is created.

Acknowledgment

N/A

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