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Deep Learning based categorization of modulation methods for wireless communications

[1]E. Vargil Vijay, [2]P. Venkata Ramireddy, [3]M. Jubeda, [4]K. Padmaja, [5]N. Venkateswarlu

[1]Assistant Professor, [2]Student, [3]Student, [4]Student, [5]Student
[1]Electronics and Communication Engineering,
[1]Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, India

Abstract: Deep learning, a novel approach which is a subset of machine learning, has demonstrated exceptional performance in the processing of images, voices, and natural language. Researchers haven't yet fully analyzed how DL can be used for wireless transmission, though. Recently, it has become more common to use DL technology for wireless communication uses. This article's suitability of a Deep learning-based strategy for classification of modulation methods is discussed. Applications for modulation method classification (MMC) are in wireless communication. This article proposes a deep learning-based architecture for modulation method classification which is known as Convolutional Neural Network (CNN) using swish activation along with lecun_normal, lecun_uniform kernel initializers and various optimizers. We showed that the suggested architecture for modulation classification methods using deep learning works better than the conventional modulation classification methods.

***IndexTerms* - Machine learning (ML), Deep Learning (DL), Modulation Method Classification (MMC), Convolutional Neural Networks (CNN).**

I. INTRODUCTION

Classification of modulations automatically is a crucial element over a number of commercial and governmental uses. It's an important between the stages of recognition and demodulating of signals. Communication engineers face difficulty in implementing cutting-edge information resources and systems for military uses in a crowded electromagnetic spectrum. The unwanted signals need to be tracked down, recognized, and jammed, And the friendly signals should be safely transmitted. These signals' spectral ranges may extend from the milli-meter frequency band and their formats may range from straight forward narrowband systems to wideband systems. Real-time interception of signals and their processing, which is essential for decision making regarding electronic warfare operations and other calculated steps raises the need for advanced techniques in such circumstances. The method of automatically identifying a signal's modulation type is known as automatic modulation classification (AMC). The three major stages of modulation recognition are pre-processing of data, feature extraction from signals, and classification pre-requisites. After signal down conversion, data pre-processing involves estimating the carrier and symbol rates to produce a variety of pertinent data for subsequent operations [18]. AMC is referred to as blind AMC when the pilot data is not recognized in the received signal. The finest AMC strategies have been determined through a variety of studies. In general, likelihood-based [1], [3] and feature-based [2], [4] approaches make up the suggested solutions. Although the DL is extensively researched across a broad range of application domains, its application in communication networks and systems has not received as much attention. There has been some documented work for modulation method classification using the deep learning, including [4]-[6]. Development of Novel techniques is that the key goal of this research is to describe the modulated impulses in the data set forms for a neural network composed of convolutional neurons. (CNN). Thanks to the advancements in big data processing and new evolutions in hardware, deep learning is a new area of machine learning (ML) [6]. When extracting high-order characteristics from data, DL architecture can use more levels of non-linear processing units in succession than traditional ML architectures can. In general, DL excels at identifying features of higher order and is the process of mapping inputs with outputs for DNN. The lengthy training period is one of the main issues confronting deep neural network-based machine learning algorithms. For instance, training three Nvidia Tesla P100 GPU chips on the problem at hand would require about 40 minutes even for the straightforward CNN architecture in [7]. Convolutional Networks (convnets) have proven to be quite effective at tasks like classifying handwritten digits and detecting faces. Convolutional neural networks (CNNs) have supplanted other machine learning techniques for the recognition of visual objects. Although they were first introduced more than 20 years ago [10]-[11], advancements in computer hardware and network architecture have only lately made it possible to train genuinely deep CNNs. As a result, it has become highly difficult to use such type of algorithms in real-time, where online training is required to redesign the network in response to shifting environmental factors. Application of deep learning to independent wireless communication systems, which are expected in next-generation networks, would require a reduction in training period when compared to current methods. In such networks, it is apparent that machine learning algorithms needs to be trained on a regular basis to account for changing environmental conditions. Therefore, the problem of cutting down on training time becomes crucial for these algorithm success [7]. In order to minimize spectral variation, the model we suggest involves feeding of signal features as input, in view of put some CNN network levels into the sequential framework. The result of the CNN layer is passed to a few Long Short Term Memory (LSTM) levels in order to lessen temporal variations. Then, the results of the last LSTM layer serves as the stimulus for some Dense Neural network layers which are fully connected. A summary of a few of the latest algorithms that are published is provided below. [9] distinguishes between the digitally modulated signals using both the pattern recognition approach and the decision-theoretic technique. In the view of improving the accuracy of classification, the CNN models should take greater complexities of computations and larger structures, which are deeper and broad models, into account. Thus the trade-off of training time needs a considerable investment in hardware, computational memory [12]. It has been suggested that collective learning approach can aid in maximizing the benefits of individual examples. In fact, it can incorporate a number of straightforward techniques while yet improving modulation classification precision in comparison to a big model. A DL network based on autoencoders and soft-max regression is presented in [13] to recognize communication signals with various modulation schemes, including FSK, PSK, ASK, QAM, and MSK. The method can recognize six different types of digital signals from the chaotic environment, including 16QAM, 64QAM, and 256QAM in QAM family and QPSK, BPSK, 8-PSK [20]. A novel approach utilizing GP and KNN has been used in this work [21]. To increase the classification accuracy, the procedure has been split into two phases. For the purpose of categorizing the aforementioned modulations, two trees have been constructed, one for each stage. At the first step, a single tree is constructed to categorize BPSK, QPSK, and QAM-16/QAM-64. In the second step, another tree is made to categorize QAM-16 and QAM-64. Using a public dataset and 11 widely used modulation techniques, we assess the detection performance of the suggested frameworks. Additionally, the suggested frameworks' recognition performance is contrasted with that of the most recent CNN-based method reported in the literature [14]-[16]. The instantaneous values of amplitude, phase and frequency serves as the foundation for the characteristics that we chose for our research. It makes use of features that can categorize a variety of modulation patterns, and the process of extracting those features is not computationally difficult. Therefore, hardware execution is possible. These features' performance at different SNR regions is discussed in the literature [4], but not under different fading circumstances. While dealing with smaller datasets under ideal conditions, ML is a viable option for modulation classification [17]. For a number of reasons, including the advantage of working with higher dimensional datasets and applicability for practical applications, AMC switched from ML to DL. The DL deals with the concept of simulation of the human brain and its mechanism. Of late, there haven't been any SLR on AMC explicitly using new DL techniques. Following is a small summary of a few survey articles' highlights.

1) The comprehensive overview of recent improvements in signal representation and data pre-processing for Classification based on variation using deep learning available in this research emphasizes the critical relationship between the categorization job and the Deep Learning (DL) tool.

2) In this Four sets of DL-based modulation identification techniques have been identified in this article based on the signal representation techniques: the representations of features, sequences, images, and mixed representations

3) This article provides thorough instances of all category of the signal interpretation which may operate in a way of springboard over additional research in the classification of DL-based modulations.

4) This article discusses the benefits and drawbacks of each signal representation method, which is crucial for planning DL-based modulation classification studies in the future.

When there is a mismatch between the model and the real communication system, classification accuracy suffers. Since accurate system models are difficult to determine in real-world situations, this method performs worse when there is a model mismatch [19]. This article provides an overview of the AMC and the features, classifiers that can be used in it. This will make it easier over designers to select the right algorithms for their intended uses. Additionally, this study is anticipated to assist fresh entrants in the area in identifying the restrictions connected to the FB-AMC techniques which are currently in use and to make way for the development of fresh AMC concepts.

II. PROPOSED MODEL.

A popular Deep Learning architecture for image classification and recognition tasks is the neural network with convolutions (CNN). There's a number of layers, including completely connected layers, convolutional, and pooling layers. To be able to obtain features from the input picture, the convolutional layer uses filters. In order to lessen computation, the layer of pooling down samples the image, the fully connected layer then makes the final prediction. With the help of gradient descent and back propagation, the network learns the best filters.

1. Input Layers: Data are fed into our model at this layer, which is why its called the input layer. The total number of characteristics in our data is represented by the same amount of neurons in this layer.

2. Hidden Layer: The concealed layer receives the information from its input level, which is the layer above it. Depending on the method we use and the volume of the data, there might be the amount of covert levels. Although an amount in of synapses every

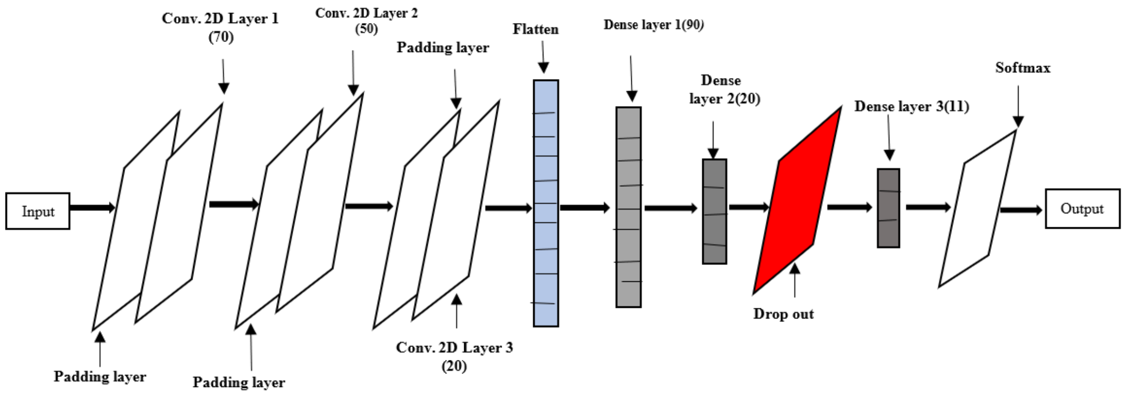


Fig.1 Proposed diagram based on CNN

hidden layer may vary, they all exceed the total of the features. The network is nonlinear because each layer's output is equivalent to that of the network before it plus biases and learnable weights.

3. Resultant Layer: Combining the outcomes of the concealed layer with this layer using a logistic function, such as sigmoid or SoftMax, to obtain a likelihood number for every class of result. In the following step, known as feedforward, the data is then fed into the model to receive the output from each layer. The error is subsequently calculated using an error formula, such as cross-entropy, cube loss error, and others. After that, the factors are calculated and re-injected into the model. The technique that is utilized to cut down on waste in general is backpropagation.

Convolutional neural networks (CNNs) have the following benefits:

• Effective at identifying patterns and features in images, videos, and audio data.
• Resistant to scaling, rotation, and translation invariance.
• End-to-end training eliminates the need for feature separation by hand.

Convolutional neural networks (CNNs) have drawbacks.

• Expensive to teach computationally and memory-intensive.
• If insufficient data or the right regularization is not used, it may be prone to overfitting.
• Demands a significant quantity of labelled data.
• Interpretability is constrained, making it challenging to comprehend what the network has discovered.

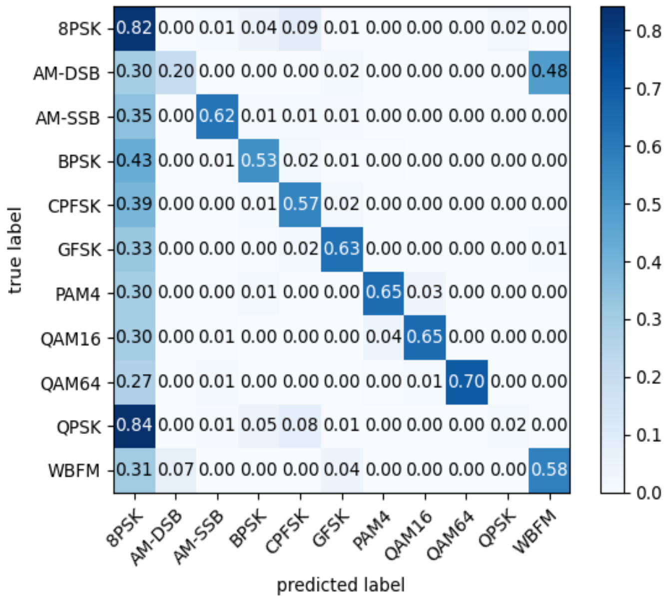
Fig.1 represents the suggested model's performance. As data is fed to the convolutional layer, which generally represents the dime matrix of the data provided. The next layer is the 2-dimensional convolutional layer which is sometimes called as feature extraction later which has the dimensions of 1x3. Here zero padding (0,2) is applied to the convolutional layer. And immediate next layer is the convolutional layer 2 is used which consists of 50 which is a 2d layer of 2x3 dimension. And next the convolutional layer 3 which contains 20 and its size is of 3x3 dimension. The next layer to the convolutional layer is the flatten layer, which has the purpose of flattening all of the two-dimensional arrays from aggregated feature maps into a solitary, lengthy, steady linear vector. The entirely linked structure is then given the flattened matrix in order to categorize the supplied data. In this article activation function like swish along with lecun_normal, lecun_uniform kernel initializers have been used.

The dense layer, a simple layer of neurons, receives information from every neuron in the layer beneath it. A dense layer is used to categorise the provided data, which is various types of modulation techniques, in accordance with the output of the convolutional layers. There are 4 dense layers present in it. The dense layer1 consists of 90 neurons and dense layer 2 consists of 20. Following the dense layer 2 is the drop out layer which acts as a mask that leaves all other neurons unaltered while nullifying some neurons' input to the following section. The last layer which is dense layer 3 consists of 11 neurons because we need to classify 11 different types of modulation techniques. Softmax layer is the last layer of the proposed model. The softmax layer acts as activation function in the classification problems of multi-class networks where more than two identifiers require class membership. It is mainly used to classify the data when more than two class labels are present and then classify the data according to the data label.

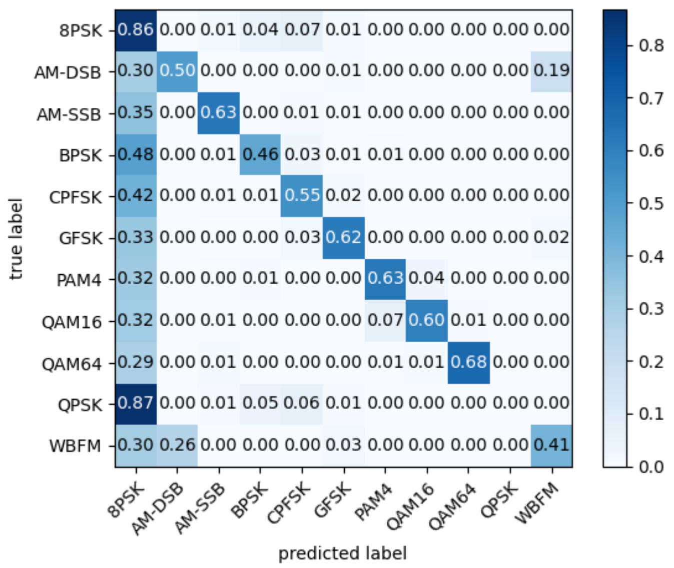
III. RESULTS AND DISCUSSION

In conclusion, confusion matrices are used to assess an identification model's efficiency, and activation functions are utilized for adding non-linearity to a neural network model. While it is unrelated to the process of creating a confusion matrix, the choice of optimizer can have an effect on a model's success. An optimizer refers to the method that alters a model's characteristics to minimize the loss function in the context of the machine learning process. A machine learning model's performance can be considerably impacted by optimizer selection. Though it is irrelevant to the method for building a confusion matrix, the selection of an activation function may have an effect on a model's success. Since different optimizers like Adam, RMSprop have differing confusion matrices, addressing them may not be proper. Adam is a dynamically adaptable optimization method that bases its learning rate on gradients. It works well for using huge datasets to train deep neural networks. The rate of learning of the adaptive optimization method RMSProp is adjusted based on the size of the most recent gradients. Large datasets may be used to train neural networks with deep layers effectively. By careful observation, we can be to clearly identify that the confusion matrix of the optimizer Adam has high accuracy when compared with confusion matrix of other optimizer RMSprop. The confusion matrix of different optimizers at SNR level of 18dB is shown below.

A. Confusion matrix of True label vs Predicted label



(a)

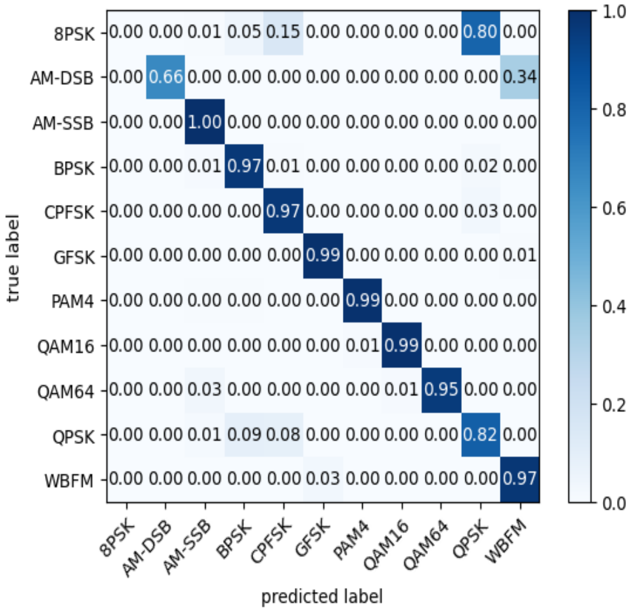


(b)

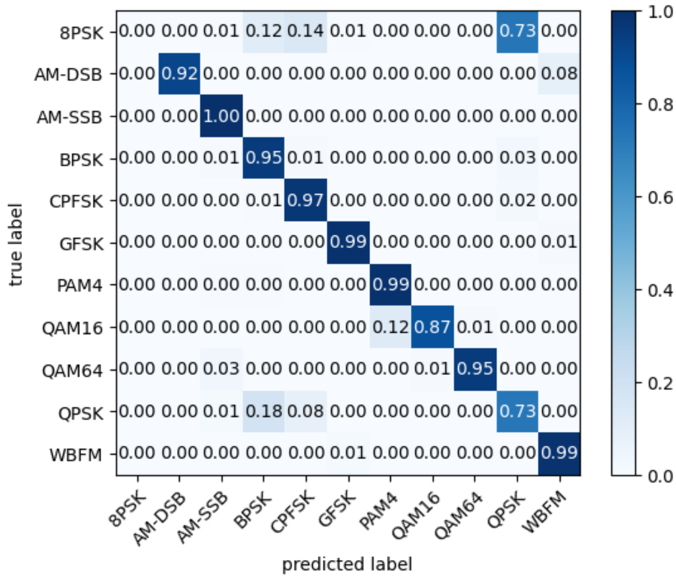
Fig. 1. Confusion matrix of Modulation classification using (a) RMSprop, (b) Adam

Here by using only one activation function i.e., swish we can calculate the accuracy of modulation classification. The primary use of an activation function is to change the linear data into non linear since in our practical scenario we are dealing with the data which is non-linear in nature. And two optimizers have been used with swish. Both of Adam and RMSprop are adaptive learning rate algorithms, which means that they change the rate at which each parameter learns in response to the previous gradient data. Because of this, they are very useful for deep learning models with a lot of parameters. In conclusion, employing Adam or RMSprop with the swish activation function is a legitimate method for deep learning models and may enhance performance. The above Fig.1 represent the overall confusion matrix of all the modulation techniques thar we are going to find in this paper. The primary goal of this project is clearly represented in this overall confusion matrix. we would need to train the model on a labelled dataset of signals with known modulation types and test it on a different dataset in order to produce a confusion matrix for a particular AMC model. The model's performance on the particular datasets utilized would determine the confusion matrix that was produced.

B. Confusion matrix of different activation functions at SNR of 18dB



(a)

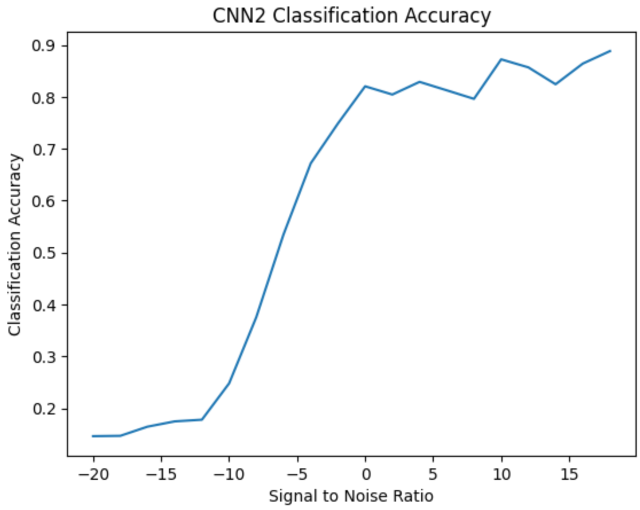


(b)

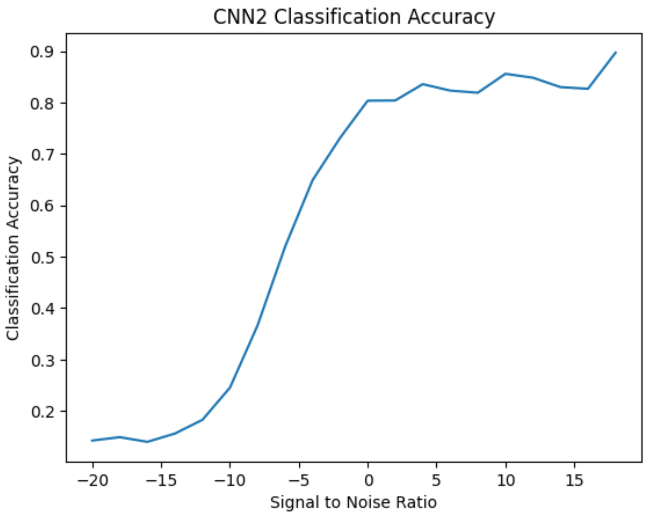
Fig. 2. Confusion matrix at SNR of 18dB (a) RMSprop, (b) Adam

The matrix of confusion is a helpful tool to evaluate a classification model's effectiveness since it gives a more thorough view of the model's performance than basic accuracy metrics. You may correct the model's faults by consulting the confusion matrix to determine where they are occurring. Here, we obtain confusion matrix at each value of SNR. The accuracy increases from low value of SNR to high value of SNR and so that it is represented in the confusion matrix of each SNR value. Confusion matrix generally represent the accuracy performance of the model. The confusion matrix in an issue of multiple classes would be a square matrix with every column and row denoting a distinct class. Metrics like precision, recall, precision, accuracy, and score F1 are frequently used to evaluate the efficiency of AMC algorithms since they help build confusion matrices. For each form of modulation, the confusion matrix displays the number of instances that were properly categorized as well as the number that were incorrectly labelled. The matrix's entries reflect the number of samples that were identified as being in each class and therefore belong to those classes. The computational cost of computing the gradient of the swish function in comparison to other activation functions must be taken into account, too. From the figure shown below we can clearly understand that the classification accuracy is accurate with Adam when compared to other optimizer by using activation function swish. The amount of percentage of accuracy increases as the SNR value increases. We have noticed that at low SNR value of -20dB the percentage of the accuracy is low and as the SNR value increases the amount of percentage of accuracy has increased. At SNR value of 18dB, we observed the percentage of accuracy has increased at good level as we compared it with the accuracy that we have obtained at -18dB.

C. Classification Accuracy vs SNR



(a)



(b)

Fig. 3. Classification accuracy vs SNR of different Optimizers at 18dB

We are able to train multiple models with the same development but different optimizer and assess how they perform on a test set to examine the accuracy of classification of neural network models using various activation parameters.

D. Percentage of Classification Accuracy of different values of SNR

The above table 1 represent the accuracy of classification at different SNR levels of different optimizers for the activation function swish. From the above tables it clearly represent that at higher values of SNR, the accuracy of classification is good and at lower values of SNR, the classification accuracy is low. From the table 1 it is observed that at SNR value of -18dB the percentage of accuracy is 14.70% for RMSprop and for Adam it is 14.89% which is slightly higher than RMSprop. From the below table 1 we can conclude that by careful observation the accuracy of Adam is higher than the precision accuracy of RMSprop. Thus we can conclude Adam gives better precision than RMSprop.

The CPFSK modulation class confusion matrix values have been described below.

False Omission Rate= 0.075
True Positive Rate= 0.567
False Negative Rate= 0.43
False Positive Rate= 0.021
True Negative Rate= 0.97
Positive Likelihood Ratio= 25.85
Negative Likelihood Ratio= 2.26
False Discovery Rate= 0.17
Negative Predicted Value= 0.92
Diagnostic Odds Ratio= 11.42

SNR (dB)	Accuracy (%)	
	RMSprop	Adam
-20	14.64	14.24
-18	14.70	14.89
-16	16.47	13.98
-14	17.48	15.59
-12	17.81	18.26
-10	24.81	24.53
-8	37.58	36.6
-6	53.50	51.91
-4	67.19	64.89
-2	74.86	73.12
0	82.03	80.33
2	80.44	80.37
4	82.88	83.55
6	81.25	82.30
8	79.61	81.89
10	87.22	85.56
12	85.67	84.81
14	82.42	82.98
16	86.40	82.66
18	88.81	89.68

TABLE 1: CLASSIFICATION PRECISION OF DIFFERENT OPTIMIZERS WITH SWISH ACTIVATION FUNCTION AT VARIOUS SNR VALUES

IV . CONCLUSION AND FUTURE SCOPE

This article explores the concept of categorizing communication modulation methods using CNN. This suggested approach shows good performance in modulation method classification at various SNR levels. This avoids the difficulty of manual feature selection at receiver side. The classification precision of a neural network can be greatly affected by the selecting of optimizers with activation function swish. In overall, there is no "best" activation function for every scenario since the best option will differ depending on every aspect of the dataset and model organization. Here by using different optimizers a good amount of accuracy has obtained which is 89.68% with Adam optimizer. Whereas the classification accuracy of swish activation with optimizer RMSprop is 88.81% which is low compared to Adam. We have achieved good classification accuracy at high SNR about 18 dB compared to low SNR. We would like to work on it further using more sophisticated CNNs, like ResNet33, with a variety of feature maps (channels), using a large dataset, like RadioML 2018.01A, which is based on actual radio transmissions.

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