Deep Learning-Based Spectrum Management to Enhance the Performance of Cognitive Radio Network Using MobileNet

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Abstract- Cognitive radio (CR) is a leading-edge technology in fifth-generation (5G) network. CR network (CRN) performance can be augmented by effective implementation of spectrum management, which is a decisive function. Signal classification plays a critical role in enhancing spectrum management. Deep learning-based spectrum management (DLSM) is a transformative technology to enhance the performance of CRN. The present work proposes a DLSM using a predefined convolutional neural network (CNN) architecture, MobileNet. The proposed DLSM was developed using a dataset with 1000 constellation diagrams of several digital modulation schemes at a signal to noise ratio (SNR) = 10 dB. The dataset was divided in to 60% for training, 20% for validation, and 20% for testing. In the proposed DL model, the dataset is pre-processed, and feature extraction is conducted using convolution layers; then, classification of images is accomplished using fully connected layers. The results outperformed with 89.4% accuracy, 90% precision, 89% recall, and 89% F1 score. The proposed DLSM exhibits substantial waveform classification performance; hence, it can be recommended for spectrum management in CRN. The dataset was generated and the work implemented using the open-source Python programming language and the licensed Colab Pro platform.

Indexed Terms- Cognitive radio network, deep learning- based spectrum sensing, CNN, accuracy, confusion matrix, AUC.

I. INTRODUCTION

5G networks experience extensive challenges in optimizing limited spectrum resources due to the speedy growth in wireless devices, and their integration with CRN is an advanced technology for attaining effective spectrum utilization [1, 2]. The key functions in CRN are depicted in Figure 1.

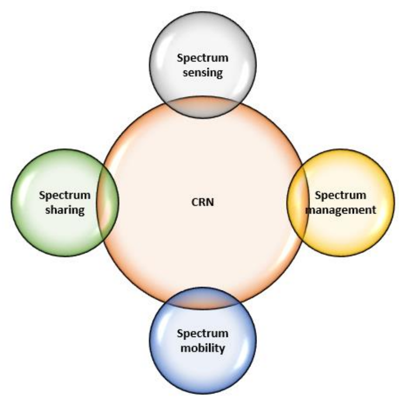

Figure: 1 Key functions in Cognitive radio

In CRN, spectrum sensing is conducted by SU (unlicensed user) to know the status (idle or occupied) of the primary users (PUs) [1], [3-5]. Spectrum management is done to select the favorable frequency for transmission based on factors like type of modulation and SNR. Hence, signal classification is a decisive function in spectrum management. The spectrum mobility maintains the connectivity without prejudice to the function of PU. If a PU uses the channel, the CR can seamlessly switch to other channels. Spectrum sharing is responsible for sharing available spectrum with other SUs without interferences.

Signal classification performance in spectrum management can be enhanced using deep learning models. MobileNet, a pre-defined CNN developed by researchers at Google in 2017 [6], was employed as a deep learning (DL) model in the present work. It consists of several layers as depicted in Figure 2.

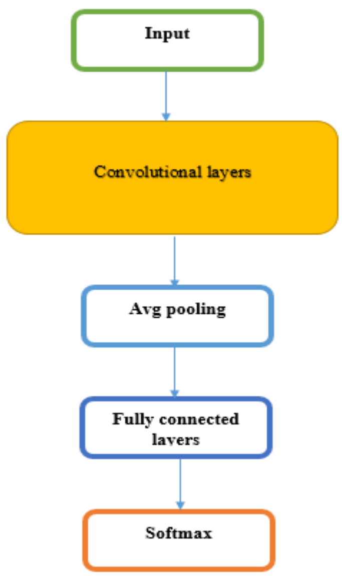

Figure 2: MobileNet architecture

The MobileNet begins with an input layer, corresponding to RGB channels. MobileNet employs depth-wise separable convolutions that significantly reduce computational complexity while maintaining accuracy. The convolutional layer in the CNN architecture is responsible for extracting significant features of the image [7]. The output of the convolutional layers is then passed to the avg pooling layer, which reduces the spatial dimensions of the feature maps by averaging values within pooling regions. This not only reduces computation but also helps summarize the most important features from the input. The reduced feature maps are then flattened and passed to the fully connected layers, which map the feature vector into scores for each target class. Finally, a Softmax layer converts these scores into probabilities, enabling multi-class classification.

Daldal et al. [8] developed a deep learning-based automatic recognition of distorted digital modulation signals. The experimental findings exhibited remarkable performance. A novel technique that employs an interference-based two level data augmentation method for automatic modulation classification was suggested in [9]. Doan et al. [10] proposed a deep learning-based eight modulation classification, achieving a classification rate of around 87% at 0 dB SNR. Peng et al. [11] proposed a modulation classifier using constellation diagrams, utilizing AlexNet and GoogleLeNet to classify eight digital modulation schemes. Further, a literature survey [12-14] was conducted to explore the key functions and the enhancement methods of CRN. Furthermore, various CNN-based models [15-19] were reviewed to investigate the classification challenges. The literature review provided valuable insights to develop the present deep learning framework.

The remaining part of the work is organized as follows: In section II, the proposed deep learning model is presented, and Section III incorporates the methodology. Section IV discusses the results, and finally, the conclusion and future scope are summarized in Section V.

II. PROPOSED WORK DEEP LEARNING MODEL

The proposed DL model that is integrated into the spectrum management function of CRN is depicted in Figure 3. Initially, the dataset undergoes a pre-processing that includes normalization to ensure uniform data ranges and scaling to eliminate noise.

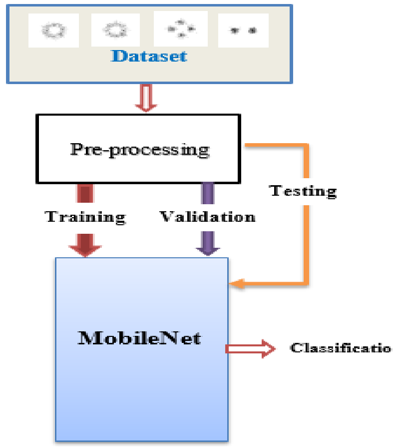

Figure 3: Proposed deep learning framework

The model is created using training and validation dataset. The feature extraction is conducted to capture significant features using the layers in MobileNet as discussed in the preceding section. Fully connected layers classify the images in the dataset according to the type of modulation. The created model was tested on test data, and the performance of the proposed model is presented in the subsequent section.

III. METHODOLOGY

The proposed model was created using an open-source programming language, Python 3. It includes several libraries like Keras for model construction, TensorFlow for backend operations, NumPy and Pandas for data pre-processing, and Scikit-learn for deriving the evaluation matrices. Matplotlib and Seaborn were utilized for data visualization. The model presented in the preceding section was executed on a licensed service, the Google Colab Pro platform, which provides advanced computational capabilities. Specifically, the Colab Pro environment includes 2 TB of storage, 25 GB of RAM, and access to an NVIDIA P100 GPU [20].

The methodology of this study revolves around dataset generation, model selection and architecture, training, refining, and performance evaluation. The dataset of 1000 constellation diagrams for four modulation schemes, such as binary phase shift keying (BPSK), quadrature PSK (QPSK), 8-ary PSK (8PSK), and 16-ary PSK was generated at SNR = 10 dB. The sample constellation diagrams for each class are shown in Figure 4.

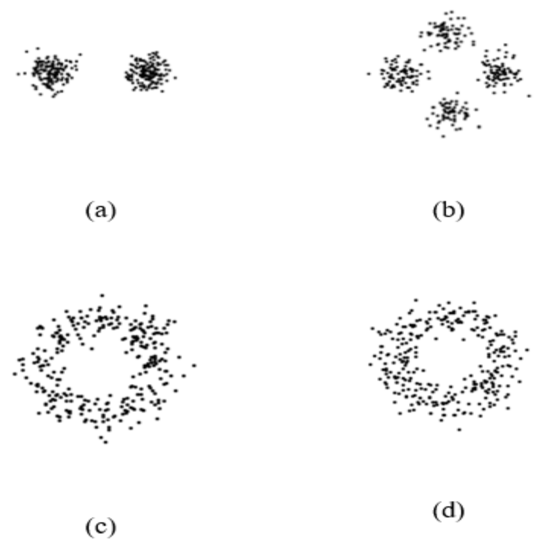

Figure 4: Sample constellation diagrams at SNR = 10 dB
(a) BPSK (b) QPSK (c) 8PSK (d) 16PSK

These images were divided into training, validation, and test sets in a 60:20:20 ratio. Each modulation type contributed 250 images, resulting in a dataset of 1000 images. Constellation points for each modulation were generated based on their mathematical definitions at SNR = 10 dB.

The MobileNet architecture was employed due to its lightweight design and efficiency, suitable for resource-optimized CRN environments. The trained model was evaluated using metrics such as accuracy, precision, recall, and F1-score. AUC and Confusion matrices are also analyzed to understand superior classification performance of the model.

IV. RESULTS AND DISCUSSIONS

The hyperparameters such as learning rate, number of epochs, and batch size in the fully connected layers were refined during training and found to be 10^{-4}, 32, and 10, respectively, with stochastic gradient descent optimizer. The created model was evaluated on test data, and the performance metrics are given in Table

1. The performance of each modulation scheme can also be visualized in bar-graphs (Figure 5).

Table 1: Performance of the proposed DL model

Accuracy	Precision	Recall	F1 score
89.4%	90%	89%	89%

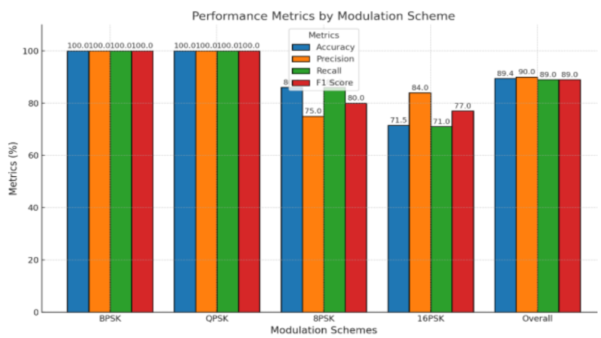

Figure 5: Class-wise performance of the proposed model

This model's robust discriminatory ability can be perceived in Figure 6.

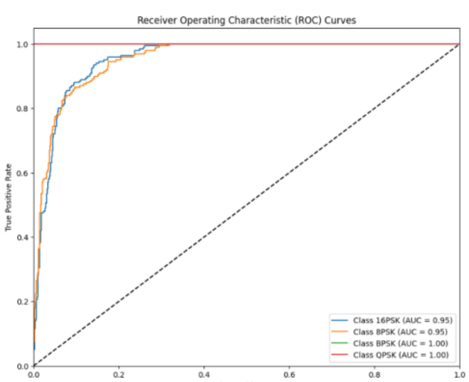

Figure 6: Area under the curve of the proposed DL model

It can be observed that the model achieved an AUC of 97.5%, i.e., it correctly ranks the images in 97.5% of cases.

Additionally, a confusion matrix is presented in Figure 7 to confirm the classification capability of the present work. In addition, the confusion matrices for each class are depicted in Figure 7(a):(d)

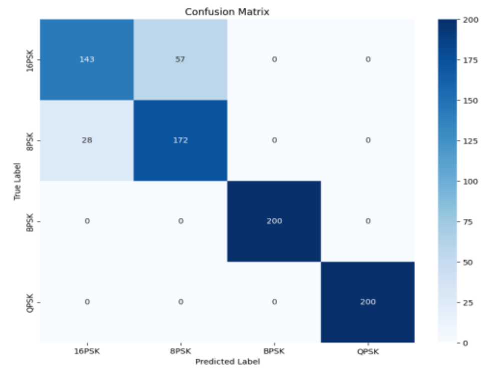

Figure 7: Overall confusion matrix of the proposed DL model

According to the confusion matrices, both the BPSK and QPSK classes show perfect classification, with all 200 samples correctly classified and no misclassifications. In 8PSK, 172 samples are correctly classified, while 28 are misclassified. For the 16PSK class, there are 143 perfectly classified samples (true positives) and 57 misclassified.

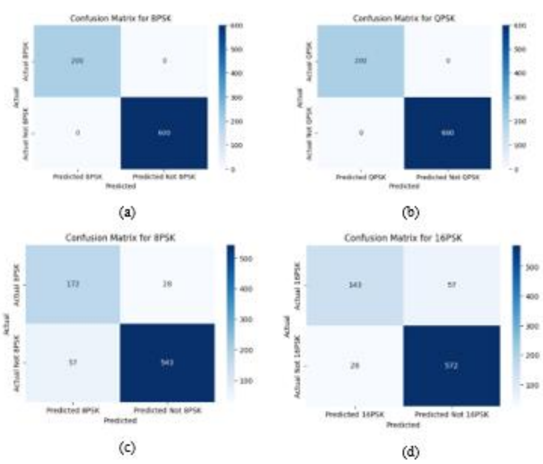

Figure 8: Class-wise confusion matrices of the proposed DL model

According to the sample constellation diagrams presented in the preceding section (Figure 4), the noise effect increases from BPSK to 16PSK, which are core principles of wireless communication [21].

Thus the confusion matrices provide a clear visualization of the model's strengths and limits across varying signal complexities.

The performance metrics can also be derived from Equations (1-4) [22].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\,Score = \frac{2TP}{2TP + FP + FN} \quad (4)$$

Where
TP = actual positive; TN = actual negative
FP = false positive; FN = false negative

The modulation classification capability of the present work can enhance the performance of cognitive radio by effective spectrum management, which can optimize the communication resources such as bandwidth and power.

We published the Python code of the present work on the Kaggle [23] and the GitHub websites [24].

V. CONCLUSION AND FUTURE SCOPE

This paper proposes a deep learning-based spectrum management to enhance the performance of the cognitive radio network. A pre-defined CNN architecture, MobileNet, was employed to classify the modulation schemes, resulting in effective spectrum management.

The proposed model was refined by optimizing hyperparameters in fully connected layers and found to be learning rate of 10^{-4}, a number of epochs of 32, and a batch size of 10. The created model was evaluated on test data, and the results outperformed with 89.4% accuracy, 90% precision, 89% recall, and 89% F1 score. Additionally, the distinguishability of the proposed model is confirmed using a confusion matrix. The proposed DLSM exhibiting enhanced performance in modulation classification can be recommended for effective spectrum management within CRN.

We published the Python code of the present work on the Kaggle [23] and the GitHub websites [24].

The robustness of the proposed system can be enhanced, further by incorporating variable SNR levels into the dataset. Additionally, integrating real-world data from software-defined radios can validate the model's performance in practical scenarios.

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