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LSTM-BIGRU based Spectrum Sensing for Cognitive Radio

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Abstract

There is a shortage of wireless spectrum due to developments in the area of wireless communications as well as the number of users that are using resources. Spectrum sensing is a method that solves the issue of shortage. Deep learning surpasses classical methods in spectrum sensing by enabling autonomous feature learning, which enables the adaptive identification of complicated patterns in radio frequency data for cognitive radio in wireless sensor networks. This innovation increases the system's capacity to manage dynamic, real-time circumstances, resulting in increased accuracy over traditional approaches. Spectrum sensing (SS) using LSTM-BIGRU with gaussian noise has been suggested in this article. Long-term dependencies in sequential data are well- preserved by LSTM due to its dedicated memory cells. In addressing and managing long-term dependencies in sequential data, BIGRU's integration enhances the efficacy of the model as a whole. To conduct the investigation, RadioML2016.04C.multisnr open-source dataset was utilized. Whereas, by using RadioML2016.10b open-source dataset, QAM64, QPSK and QAM16 performance evaluation has been investigated. The experimental findings demonstrate that the suggested Spectrum Sensing has better accuracy on the dataset particularly at lower SNRs. The improved spectrum sensing (SS) performance of our suggested model is shown by the evaluation of performance indicators, such as the F1 Score, CKC and Matthew's correlation coefficient, highlighting its potency in the field of spectrum sensing applications.

Keywords: Spectrum Sensing, wireless communication, CKC, MCC coefficient

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1. Introduction

The radio spectrum bands used for wireless communication are frequencies, and spectrum sensing identifies their availability and occupancy state. Cognitive radio networks heavily rely on spectrum sensing, which enables reliant users to access free frequency bands to optimize spectrum efficiency [1]. Cognitive radio has been suggested to optimize the utility of wireless networks' spectrum resources.

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The use of spectrum sensing strongly influences cognitive radio. Traditional spectrum sensing methods focus on identifying characteristics in a signal received at a given place through techniques like cooperative spectrum sensing, more accurate spectrum sensing is now possible using DL [2].Conventional detectors with their limitations include matched filters, energy detectors, and cyclostationary feature detectors [8] [9].

The requirement for spectrum for 4G and 5G networks has grown due to the widespread use of mobile devices. The present spectrum dilemma is primarily due to the wasteful usage of licensed frequency bands. Cognitive radio (CR) technology has gained popularity as a solution to this issue. The licensed spectrum of primary users (PUs) is available to secondary users (SUs) via CR Wireless communication has typically relied on specialized knowledge and too simplistic models to extract characteristics from the spectrum. These methods mainly depend on human operators and extensively use preconceptions [7]. SUs are in charge of ensuring that their access doesn't interfere with PU signals [5]. Spectrum sensing (SS), figure out if PUs is on or off, has been a challenging issue, with energy detection being the most preferred method because of its simplicity. There have been many recommendations in recent years to apply machine learning (ML)-based SS algorithms to improve the exposure performance for cooperative radio frequency sensing (CSS) [6]. The SUs in the spectrum- aware radio network monitors the frequencies in use and, when appropriate, utilize the free channels [5]. Multi-layer perceptron (MLP) networks are among the most widely used deep learning and machine learning frameworks incorporating spectrum sensing. The absence of memory components in MLP networks makes them potentially useless for time-series data. Alternatively, by extracting characteristics from the network itself, deep neural networks (DNN) provide a data-driven approach that may reduce the number of assumptions. Frequency spectrum prediction may reduce time delays by relieving the burden of spectrum sensing. Utilizing a deep recurrent neural network (DRNN) can predict the spectrum for several time slots, as present techniques can only expect the spectrum for a single or fewer time slot [3]. Both super- vised and unsupervised machine learning DNN models are now used in RFML. How- ever, supervised machine learning networks are more common since they can be con- figured to do specific tasks rather than merely looking for structure in the data. The recent outcomes show that CNN, and RNN are more effective at spectrum sensing, reducing an algorithm's complexity show how performance might be improved [2]. A vital component of the LSTM-based spectrum sensing strategy is training an LSTM network using labeled spectrum data, which imparts the network to discover patterns and correlations in the data. The LSTM network may be used for real-time spectrum sensing after being trained by feeding its received spectrum data; the network then determines whether or not a particular frequency band is open for usage [4]. LSTM networks have gained popularity for their ability to learn temporal features from sequential input.[16][17][18]. An LSTM-based SS method use the data's temporal peculiarities [19]. Spectrum-aware radio technique based on LSTM that takes use of the extraordinary learning power of LSTM networks [10] [15] to extract latent information from spectrum data, such as temporal correlations between current and timestamps [6]. Recurrent neural networks (RNNs)[16] and hybrid CNN-RNN net- works have gained popularity over the last ten years, replacing convolutional neural networks (CNNs)[12], which were previously widely employed in RFML research [13]. The Bidirectional Gated Recurrent Units (BiGRUs) neural network architecture is utilized for sequence modeling [20]. They improve conventional GRUs by pro- cessing input data forward and backward and incorporating contextual data from previous and future time steps. By taking into account bidirectional context, they provide more detailed representations and increase the model's capacity for precise prediction in sequential data tasks

2. Related Work

Convolutional operations in the convolutional neural network (CNN) extract complicated characteristics from the pre-processed input that are crucial for regression tasks, according to studies by Mahak Kalra [11] et al. The CNN's input layer must first receive the pre-processed data, which must then perform convolution operations to extract complex features relevant to regression. The model consists of layers such as the sequence layer, LSTM layer, fully connected layer, and regression layer. The LSTM layer incorporates LSTM memory cells to enhance the model's memory capacity. The CNN-RNN model suggested by this research yields the following results the rate is 0.9895, the error proportion is 0.0105. CNN and SAM-CNN detectors can manage spectrum sensing in situations with intermittent prominent signal presence, according to studies by Zhan Cong et al. [12]. Numerical findings demonstrate that the recommended detectors perform much better than the state-of-the-art detectors, with higher detection probabilities and improved ROC performance. This method also indicates that the SAM-CNN detector, which utilizes switch feature extraction from channel state data, is superior to the CNN detector in spotting abnormalities. The best performing of the other detectors achieves detection probabilities below 0.7. In contrast, the CNN and the SAM-CNN detectors achieve around 0.8 and 0.87 detection percentages with a false alarm probability (Pf) of 0.1, respectively.. The best performance of the other detectors drops to 0.55 when Pf is adjusted to 0.05, but the SAM- CNN detector retains a detection probability of around 0.84. When Pf is set to 0.05, the SAM-CNN detector improves the detection probability when compared to the CNN detector by 19%. The Generalized Likelihood Ratio Test (GLRT) was examined in the work of Q. Cheng et al. [13]. The GLRT scheme's underlying Maximum Likelihood (ML) estimations were devised and expressed in closed forms, allowing for real- time implementation appropriate for automotive applications. The main goals of this method were to evaluate algorithm performance in dynamic random processes characteristic of urban traffic applications and to advance GLRT spectrum sensing for a generic rank-K situation, where $1 \leq K < M$. The research notably addressed the complicated vehicular-application spectra that are present in areas such as New York City. In the work by M. Karimzadeh et al. [14] it was shown that the suggested system performs better with heavy-tailed Generalized Gaussian Noise (GGN) than its predecessor PCA, and the well-known ED method. The slope parameter was optimized in order to obtain this improved performance. The research used a GGD with shape parameter η=0.9 to account for noise in numerical results. This distribution is some- what heavier-tailed than a Laplacian distribution, which is generally regarded as the standard heavy-tailed distribution. The best value in the fading situation is considered. to be the same as that in the no-fading scenario, despite of the difficulty in calculating this value when the primary signal suffers fading. This presumption illustrates how difficult it may be to determine the ideal settings when there is signal fading.

3. Proposed Method

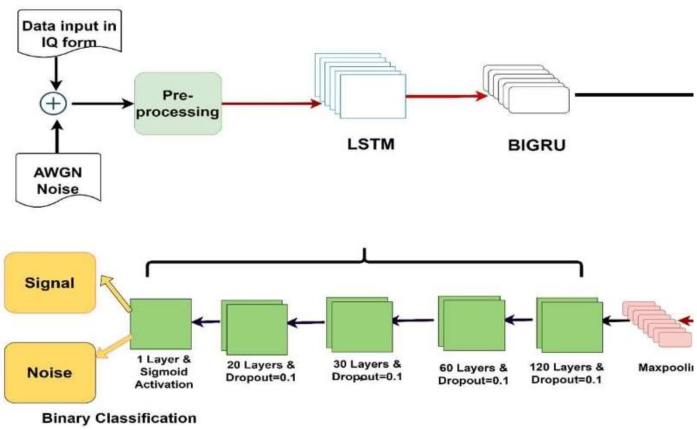

Figure 1. Proposed system Block diagram

Equation (1) gives the model a problem conceptualization. Spectrum sensing is a representation for binary classifiers. If the null hypothesis is correct, no PU exists, and noise is being picked up instead. If the alternative theory is correct, PU will be found. The additive gaussian signal in equation (1) has a mean value of zero

$$\{Y\} = \begin{cases} H_1: \{S_{\mathrm{msg}} + 5_{\mathrm{gaussian}}\} \\ H_0: \{5_{\mathrm{gaussian}}\} \end{cases} \tag{1}$$

The dataset has been downloaded from open-source websites https://www.deepsig.ai/datasets, https://www.kaggle.com where these have SNR ranges from -20dB to 18db with an increment of 2dB. In this various modulation techniques data has been included in the form of 128*2 vectors. The proposed system block diagram is shown in Fig. 1. . AWGN noise in complex form has been added to I- Q form of modulation, and after preprocessing, the data and noise are given to 24 LSTM and 12 BIGRU units. LSTM networks are primarily used for the learning, processing, and classification of data, which is in sequential form, because they can learn long-term dependencies among time steps . Let $m = (m1, m2, \ldots \ldots mz)$ be the input, z be the number of overall elements. h represents the vector of the hidden state and l indicates the input sequence position.

Here $\not{f}$, u, and o denotes the forget, input and output gates outputs given in $eqs.$ (2), (3), and (4). b indicates the bias element, U denotes the weight matrix corresponding to hidden state, $\mathbf{G}$ is the matrix of weights, δ represents memory component to store intermediate outcome which has been represented in $eq.$ (5) and in $eq.$ (6) [20]. c denotes the momentary value, ❋ denotes element wise multiplication, and σ denotes sigmoid activation. G_{frget}, G_{inpt}, and G_{otpt} denote the weight matrices [21] which belong to forget, input, output gates.

$Relu$ activation in LSTM is described in $eq.$ (7) . BIGRU operates in both directions and extracts context features in the spectrum sensing model [21][22].

$$\not{f}_r = \sigma_z(G_{frget}a_r + U_{\not{f}}c_{r-1} + b_{\not{f}}) \tag{2}$$

$$u_r = \sigma_z(G_{inpt}a_r + U_u c_{r-1} + b_u) \tag{3}$$

$$o_r = \sigma_g(G_{otpt}a_r + U_{otpt}c_{r-1} + b_{otpt}) \tag{4}$$

$$\delta_r = \not{f}\lambda_{r-1} + u_r * \frac{\mathrm{sech}(G_g a_r + U_g c_{r-1} + b_g)}{\mathrm{cosech}(G_g a_r + U_g c_{r-1} + b_g)} \tag{5}$$

$$c_l = o_r * \frac{\mathrm{sech}(\lambda_l)}{\mathrm{cosech}(\lambda_l)} \tag{6}$$

$$\mathrm{ReLU}(5) = \max(0, 5) \tag{7}$$

The output is then passed through a dense layer where the features will be extracted, and finally, sigmoid activation is used for binary classification to classify signal and noise classes. F1 Score and MCC equations have been represented in eq. (1) and (2). Where φ indicates True, and θ indicates False. Suffixes p and n indicates positive and negative respectively.

$$F1\ Score = \frac{2\varphi_p}{2\varphi_p+\theta_p+\theta_n} \quad (8)$$

$$MCC = \frac{\varphi_p\varphi_n-\theta_p\theta_n}{\sqrt{(\varphi_p+\theta_p)(\varphi_p+\theta_n)}\sqrt{(\varphi_n+\theta_p)(\varphi_n+\theta_n)}} \quad (9)$$

$$CKC\ Score = \frac{2(\varphi_p\varphi_n-\theta_p\theta_n)}{(\varphi_p+\theta_p)(\varphi_n+\theta_p)+(\varphi_p+\theta_n)(\varphi_n+\theta_n)} \quad (10)$$

4. Results and Discussions

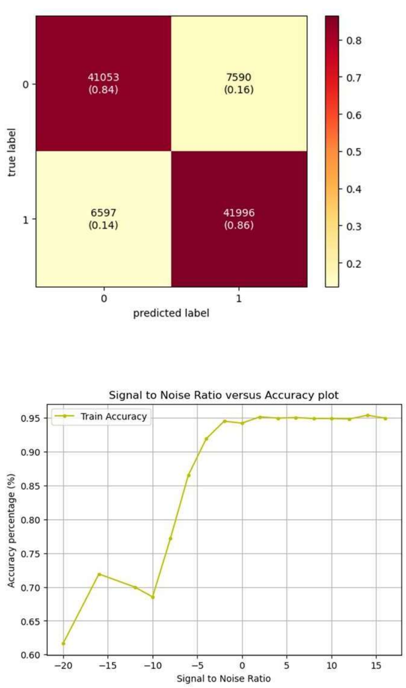

Figure 2. Confusion matrix and accuracy percentage comparison plot

The suggested method's SNR vs accuracy is shown in Fig. 2. The TP, TN, FP, and FN values have been determined using the confusion matrix. The categorization results are greater than 84% for both true positives and true negatives. This demonstrates how the model more accurately separates signals from noise. When the value is greater than -3 dB, the accuracy reaches 95%, and at lower SNR, it reaches 60%. The representation of confusion matrices in SNR wise is shown in Fig. 3. It shows that the categorization improves as SNR rises; even at lower SNRs, the classification is comparably better.

Fig. 4. shows the SNR wise comparison of Performance metrics. It has been observed that at lower SNRs the MCC value is higher. And CKC value for the proposed system is above 0.9 which indicates that the performance of the system is reasonably good at all SNR. Similarly, MCC and F1 Scores have also been indicated SNR wise. The system performance assessment utilizing the RadioML 2016.04C.multisnr dataset is shown in Fig. 2, Fig. 3, and Fig. 4. Table 1 compares the suggested method's performance metrics. When it comes to spectrum sensing, a range of performance measures provide a thorough

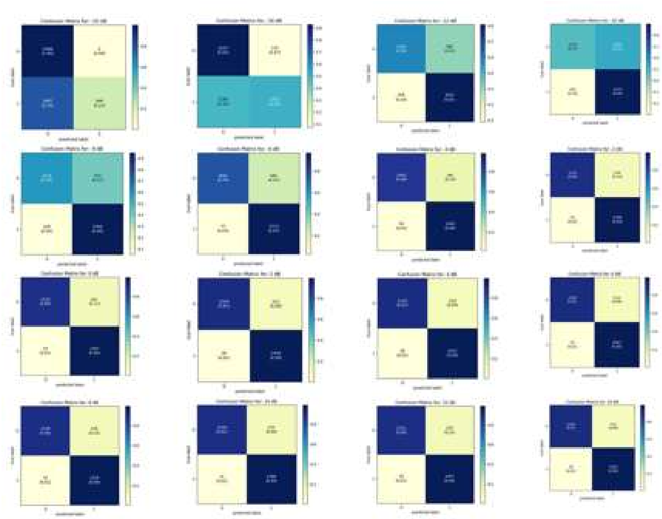

Figure 3. SNR wise Confusion matrices from -20dB to 16dB

assessment of the detection procedure. The precision value of 0.8469 indicates the dependability of properly detected cases when it comes to assessing the accuracy of positive predictions. The percentage of true positives that are mistakenly categorized as negatives, or the false omission incidence, is 0.1384, which indicates a very low incidence of missed detections. The effective sensitivity in detecting positive cases is shown by the miss rate, which is 0.1357. With an observed value of 0.1530, the false discovery rate which quantifies the proportion of false positives to all anticipated positives indicates a modest degree of overprediction. The model's ability to accurately identify negative instances is demonstrated by the Negative Predictive Value, which is calculated at 0.8615 and illustrates the accuracy of negative predictions. With a calculated value of 0.8909, the diagnostic odds ratio a thorough indicator of diagnostic accuracy offers a full evaluation of the sensing system's effectiveness. With a misclassification rate of 14.59%, which is the total error rate, there seems to be a very low number of misclassifications. The model's balance in managing false positives and false negatives is attested to by the F1 score, a balanced measure of accuracy and recall, which is given as 0.855. With a CKC score of 0.7081, which represents the classification knowledge contribution, there is a sufficient degree of discriminative ability. Lastly, the model's capacity to precisely detect positive cases in spectrum sensing applications is shown by the FMI Index, which measures the similarity between predicted and actual positive occurrences at 0.8554. . It has been shown that from Fig. 4(d) and Fig. 4(e), both misclassification rate and FOR values steadily decrease as SNR increases, and that the misclassification percentage is still higher than 60% even at lower SNRs.

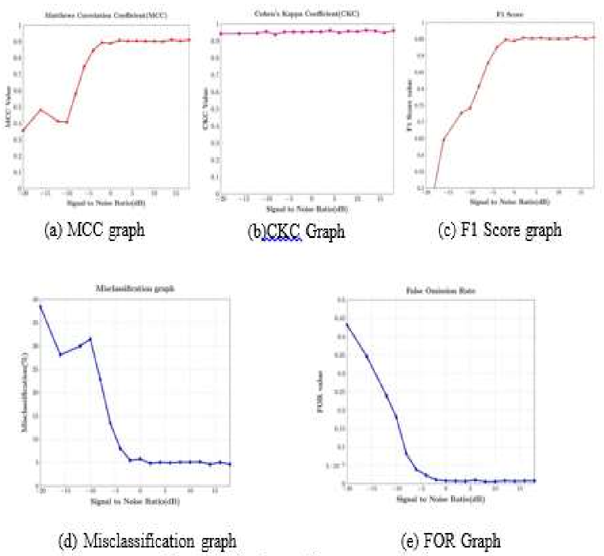

Figure 4. SNR wise performance comparison

Table 1. Performance metrics using RadioML 2016.04C.multisnr dataset

Performance Metric	Value
Precision	0.8469
False omission rate	0.1384
Miss rate	0.1357
False discovery rate	0.1530
Negative predictive value	0.8615
Diagnostic odds ratio	0.8909
Misclassification rate (%)	14.59
F1 Score	0.855
CKC Score	0.7081
FMI Index	0.8554

Using the RadioML 2016.10b dataset, Fig. 5. compares the misclassification rate (MCR), sensing error (SE), false negative rate (FNR), and false discovery rate (FDR) for QAM64, QAM16 and QPSK. Based on the acquired data, QAM64 performs better than QAM16, and QPSK for the metrics mentioned above. Specifically, QAM64's sensing error is reduced at 11.78 compared to QAM16's 14. 7, and QPSK's 18.09. Thus, in comparison to QAM16 and QPSK, QAM64 performs better in noisy environments

5. Conclusion

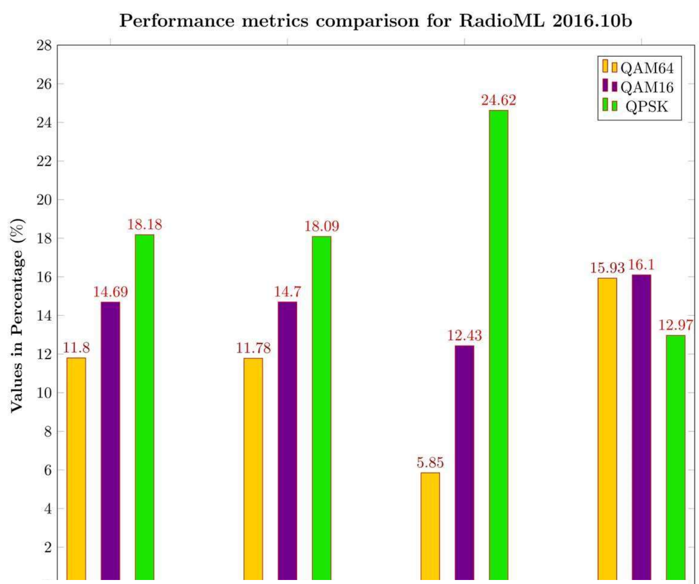

Figure 5. Performance metrics bar chart for QAM64, QAM16 and QPSK

In contrast to conventional techniques, spectrum sensing using deep learning in Cognitive Radio (CR) performs better because of advancements in AI and DL technology. This paper proposed the LSTM-BIGRU strategy as an enhanced DL-based spectrum sensing method that provides a sophisticated knowledge of spectrum sensing. Our model carefully examined performance metrics, such as MCC, F1, and CKC scores, to provide a thorough assessment of its effectiveness using, RadioML 2016.04C.multisnr dataset, and performance evaluation for QAM64, QPSK, and QAM16 have been performed using RadioML 2016.10b dataset. The suggested method was quite effective as it was not only buoyant under normal circumstances but also more flexible when Gaussian noise was present. This flexibility highlights its practical use and represents a significant progress in improving the dependability and effectiveness of spectrum sensing in dynamic communication context.

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