ESA-CGRN-A Reinventing Deep Neural Networks Using Self Attention Maps And Gated Recurrent Neural Networks For Effective Spectrum Sensing In Cognitive Radio

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Abstract

Cognitive radio has garnered significant attention in scholarly research worldwide owing to its potential to offer innovative solutions for mitigating the limited availability of spectrum utilization. Traditional approaches, including energy detectors, model-based detectors, and cyclo-stationary detectors, are employed to facilitate effective spectrum sensing; however, they fall short in achieving optimal detection accuracy. Recently, machine learning and deep learning algorithms have been integrated to execute intelligent spectrum sensing techniques characterized by enhanced detection ratios. Nevertheless, these methodologies do not adequately qualify for pure feature extraction, which is essential for improved performance. To remedy this deficiency, the present study proposes an ensemble of self-attention maps within a hybrid architecture that combines convolutional neural networks (cnn) and gated recurrent networks (gru), emphasizing the enhanced signal comprehension that may bolster efficient spectrum sensing across various environmental conditions. Comprehensive testing has been conducted to evaluate the proposed model employing the rtl-sdr interfaced with the raspberry pi model, utilizing python-based gnu radio programming to facilitate effective signal collection under diverse communication parameters, including signal-to-noise ratio (snr), modulation types, and data length. Performance metrics, such as the probability of detection (pd) and the probability of false alarms (pf), have been calculated and juxtaposed with other deep learning (dl)-based sensing systems. The results indicate that the proposed model surpasses other deep learning architectures and exhibits a crucial role in spectrum sensing, effectively addressing the pressing demand for spectrum resources.

Keywords: Cognitive Radio, Energy Detectors, Convolutional Neural Networks, Gated Recurrent Neural Networks, Self-Attention Maps.

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INTRODUCTION

In the recent times, rapid growth of wireless communication in terms of 5G and Internet of Things (IoT) has exponentially increased the spectrum scarcity [1]. To overcome the above problem, Cognitive Radio (CR) provides the more attractive insights in terms of an effective spectrum utilization. It uses the idea of spectrum sensing mechanism which detects the free bands of authorized users (primary users), by which the unauthorized users (secondary users) can access these free bands to promote the spectrum in scarcity [2]. In the past decades, traditional and non-intelligent detectors such as Maximum Eigenvalues Detector (MED), Generalized Likehood Ratio Test (GLRT) and Sun Space Eigenvalues (SSE) detectors are employed by gaining the prior knowledge of noise power from the user signals. But are used to exploit the confidence features from the different input signals that can serve as the catalyst to propel the spectrum sensing without any interference of the user signals

3. Experiments are conducted using the GNURADIO based

these methods still needs improvisation in sensing the primary users (PU) under different circumstances of high noises and different modulation techniques. Therefore, it is critical to improve spectrum sensing capability under the aforementioned conditions in order to withstand the challenging noise level situations.

It has been suggested that deep learning algorithms be used to take use of both the recent and previous data in spectrum sensing in order to utilise such spectrum sensing approaches. Many deep learning techniques [3,5,6,7] are proposed for an effective sensing of spectrums under rugged circumstances of the high noises. On the top of it, many hybrid deep learning algorithms are proposed adds the fuel for enhancement of spectrum sensing activities under rugged noisy circumstances. The suggested hybrid learning algorithms are nonetheless vulnerable to high ambient noise levels and transmission fading, which have an influence on spectrum usage, as practise has shown.

This study offers innovative spectrum sensing approaches that are motivated by the aforementioned issue. They are based on a modified hybrid architecture of Self-Attention (SA)- based Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU), where the CNN plays an important to significantly extract the spatial features and the GRU is incorporated to extract the temporal information. Furthermore, self-attention maps are integrated in both layers to eradicate the redundant noisy features that can even improve spectrum sensing schemes even under high noisy circumstances and modulation techniques. The main contribution and novelties of the paper is as follows:

1. Proposes the Spectrum Sensing framework which relies on improved version of CNN and GRU networks by integrating with the Self-attention maps. This improves the spectrum utilization even under the low SNR conditions.
2. Adoption of Self –attention maps in the CNN and GRU Raspberry Pi Model B + and compared with the other state-of-art deep learning frameworks. The proposed approach showed better performance than the other approaches in various conditions, according to the findings.

The rest of the paper is organized as follows as: 1) **Section 2** presents the problem formulation with the working mechanism of the proposed methodology. 2) The experimentation details, implementation, result analysis are presented in **Section-3** .3) finally the paper is concluded with future enhancement in **Section-4.**

Problem Formulation

It is taken into account to use many antennas for cognitive radio. In this case, the primary user signals are sent by primary user (PU) transmitters. The sample phase and the model training phase are two stages of the suggested model, respectively. In order for the network to make a choice when an unknown sample arrives, the first stage samples the main user signals, which are subsequently utilised as inputs to the training stage. Consider X(n)=[x1(n), x2(n), x3(n)..................xL(n))^T where, Signal sample length is represented by L, n=0,1,2,…..................... M-1 where M-1 indicates received signals from the various PU emitters. A binary hypothesis testing problem may also be used to describe the spectrum sensing problem.

$$H_1: X(n) = Y(n) + W(n) \quad (1)$$

$$H_0 = X(n) = Y(n) = W(n) \quad (2)$$

The signal vector Y (n) stands for the noise vectors, whereas W (n) stands for the signal vector with route loss and channel fading. As a result, the hypotheses H1 and H0 both indicate the presence of the principal user (PU) and its absence, respectively. The modified sets of the signals X are obtained by extracting the in-phase (I) and quadrature (Q) components from the received signals.

$$X_I = Real(X(n) \quad (3)$$
$$X_E = Quadrature(X(n) \quad (4)$$

Data Labelling Process

After receiving signals, signals are labelled to obtain the training and testing data which are then feed to the proposed model. The mathematical labelling of the data is represented as follows

$$X^{Training} = \{(X^1\ Y^1), (X^2\ Y^2), (X^3\ Y^3), (X^4\ Y^4) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .\ (X^k\ Y^k)\} \quad (5)$$

Where X is the input data for the proposed I-Q model, and Y is a member of the set of outputs that reflect the hypotheses H0 and H1, respectively. Equation (5) describes how the features from the training data are extracted by the deep learning architecture. Equation (5) also models how the test analysis of the deep learning architecture is based on a binary classification issue where the labels are effectively encoded using on-hot encoding.

Proposed Deep Learning Architecture

The proposed model is built using Gated Recurrent neural Networks (GRU) and Convolutional Neural Networks (CNN) with self-attention capabilities. While GRU is utilised for the extraction of temporal features, CNN is utilised for the extraction of local correlation features. In order to enhance the effectiveness of sensing, Self-Attention (SA) layers are included in both levels. To avoid data losses that might impair the network's capacity for sensing, this study uses the CNN-GRU and self-attention maps in simultaneously. The suggested model interacts with the SA-based GRU network to extract the additional temporal characteristics after including the CNN, SA layers, and SA layers for the extraction of spatial data. In order to further classify these traits, the thick layers are fed.

Self-Attention Maps

The attention map was first presented in 2014 to specify the correct terminology for sequence-to-sequence architecture. Most recent research has concentrated on using attention layers to simulate redundant features that can help with the precise categorization method. The three vectors Q, K, and V are created for each input sequence to perform the self-attention mechanism, also known as the intra-attention mechanism. As a result, the output sequences are created by transforming the input sequences from each layer. Or to put it another way, it is a method that, by utilizing scaled dot functions, translates the query to the collection of key pairs. Self-dot attention's product is calculated mathematically as follows:

$$F(K, Q) = ((K), Q^T))/(V_K)\text{^}0.5 \quad (6)$$

Self –Attention Enabled Convolutional Networks

The input data, which stands for the quadrature and in-phase components, is sent into the SA-CNN network as the first element. Four convolutional layers make up the model, which also includes fully connected networks (FCN) and self-attention maps that are incorporated at the end. The energy-correlation properties of the incoming signal are extracted by employing the first part of the suggested layer. For the purpose of extracting the intermediate feature maps, four convolutional layers and four pooling layers are employed. The self-attention layers, which can help with improved extraction, are given these intermediate characteristics next. Mathematically, energy correlation features extracted from the first component is expressed as follows as

$$Spatial\ Fetaures\ S(F) = \sum_{i=1}^{N} F(J(i) + X(i) + B) \tag{7}$$

Where B is bias factors. J (i) is the convolutional layers and X (i) is the input feature vectors.

$$X(SACNN) = Softmax\ (S(F), F(K, Q)) \tag{8}$$

Self –Attention Enabled Gated Recurrent

Networks

Nowadays, Gated Recurrent Neural Networks (GRNN) performs better extraction of temporal features compared with Recurrent Neural Networks (RNN) and Long Short term Memory (LSTM). However, RNN suffers from the disintegrating gradient problem in handling the data only for short time. In order to solve this issue, the gate architectures are specially modelled into the LSTM and GRNN models to overcome the downsides (forget gate, output gate, and input gate). LSTM contains three gate structures, but GRNN only has two (update and reset gate). From a computing complexity analysis, GRU exhibits less complex characteristics than LSTM. GRNN is introduced in this research is due to its less complex nature. To extract the temporal features, input signals as mentioned in Equation are again feed to the proposed component which consist of GRNN followed by the self-attention maps.

The GRN network extracts the temporal features which contains the diverse information that can be used for the classification. But these features contains more diverse information that may affect the training time which constitutes the overhead in the classification layer. To overcome this overhead in classification. The input features from GRN network fed to the softmax layer to generate the attention features using Equation (6) which are then fed to the feed forward classification layers.

$$P(F) = GRU\ (\textstyle\sum^{n}_{t=1}\ [x_t, h_t, z_t, r_t(W(t), B(t), \eta(tannh))] \tag{9}$$

Integrated Self-Attention (SA) with GRN Feature Extraction is mentioned as follows

$$Y = Softmax\ (P(F), F(K, Q)) \tag{10}$$

$$Total\ Features = Concat(X, Y) \tag{11}$$

Finally the features extracted from the SA-CNN and SA-GRU are concatenated(Equation 11) to form the new feature maps that can be feed to the training network The training network effectively senses the spectrum in accordance to the primary users. The binary cross-entropy function is used in the training network.

Performance evaluation

In this part, the suggested model's behavior is assessed and contrasted with that of other current methods using performance measures including F1-score, accuracy, precision, and the probability of detection and false alarm rates.

Implementation and Performance metrics:

The suggested model was trained, validated, and then tested for the performance evaluation. Prediction accuracy (Pa), precision (P), recall (R), probability of false alert (Pf) and probability of detection (Pd), are the performance measures taken into account for assessment. Pd is the probability that the principal user will really declare their presence while using the spectrum, and Pf is the probability that they mathematical formula is used to determine the performance metrics: will declare their absence while using the spectrum. Both probability were computed based on the received signals' various SNR values.

The following Prediction accuracy

$$(Pa) = (TP + TN)/(TP + TN + FN + FP) \tag{12}$$

$$\text{Precision} = TP/(TP + FP) \tag{13}$$

$$\text{Recall} = TP/(TP + FN) \tag{14}$$

$$\text{Probability of Detection} = TPU/(TPU + TNP) \tag{15}$$

$$\text{Probability of Missed Alarm rate} = TNU/(TPU + TNP) \tag{16}$$

Where TPU is for Total Primary Users and TP stands for True Positive, TN for True Negative, FP for False Positive, FN for False Negative, and Noise level signals are TNP.

Experimental Results:

deep learning algorithms, including 1D-CNN [8], LSTM [9], CNN-GRU [10], LSTM-ELM [11], DLSenseNEt [12]. A low probability of false alarm (0 to 0.1) and a low sensing error with a high probability of detection are required by the IEEE 802.22 standard for the

To show the extraordinary performance of the proposed framework, the simulation results are shown. Analyses are done to determine how characteristics like signal-to-noise ratio and various modulations affect the system. This section displays and contrasts the performance of the proposed model with that of various CNN-

intended model. Additionally, the above-mentioned parameters are used to generate the performance metrics of the proposed model, including prediction accuracy, precision, and recall.

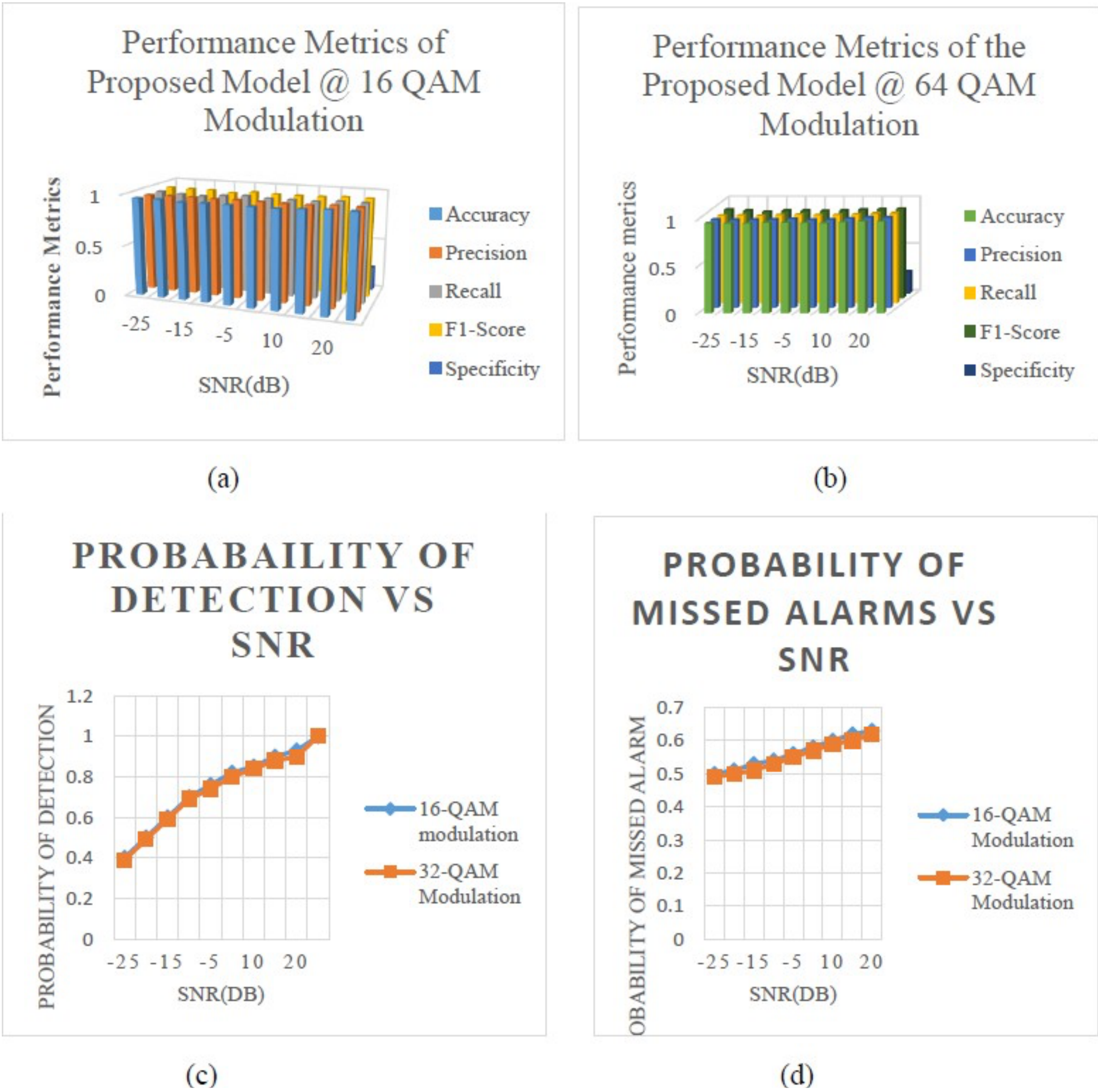

Figure 1 Performance of the Proposed Model a) 16 QAM Modulation b)32 QAM Modulation

c) Probability of Detection d) Probability of Missed Alarm Rates

Learning Architectures at High SNR environment at 16 QAM Modulation

Table1 Average Performance of the Different Deep

Algorithms	Sensing Accuracy	Precision	Recall	Probability of detection	Probability of false alarm rates
	Performance Metrics				
1D-CNN	0.85	0.834	0.820	0.820	0.173
CNN-LSTM	0.92	0.902	0.902	0.90	0.101
CNN-GRU	0.94	0.930	0.910	0.931	0.075
LSTM-ELM	0.94	0.93	0.92	0.923	0.074
DLSenseNEt	0.945	0.932	0.912	0.90	0.072
Proposed Model	0.967	0.954	0.953	0.940	0.060

Table 2 Average Performance of the Different Deep QAM Modulation Le arning Architectures At Low SNR environment at 16

Algorithms	Sensing Accuracy	Precision	Recall	Probability of detection	Probability of false alarm rates
	Performance Metrics				
1D-CNN	0.72	0.714	0.702	0.70	0.30
CNN-LSTM	0.85	0.840	0.831	0.82	0.180
CNN-GRU	0.867	0.850	0.843	0.84	0.166
LSTM-ELM	0.87	0.863	0.823	0.83	0.117
DLSenseNEt	0.89	0.883	0.893	0.89	0.110
Proposed Model	0.96	0.959	0.955	0.938	0.062

From the Figure 1 (a)-(d), it is clear that the proposed framework gives the uniform performances under the different SNR circumstances with the modulation techniques. Table 1 and 2 shows the comparative analysis between the average performances of the different deep learning based spectrum sensing techniques. It is observed that proposed framework has shown excellent sensing performance even at the low SNR whereas the sensing capability of the other model degrades as the noise level increases. The integration of self –attention maps in CNN and GRU has produced the considerable superior performances than the other models even under the high SNR with the different modulation techniques.

Conclusion and Future Scope:

This manuscript delineates an innovative deep learning architecture aimed at the efficacious detection of primary users' spectrum amidst noisy conditions. The suggested framework amalgamates self-attention maps with a hybrid configuration of Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU). The extraction of spatial features is accomplished through the application of CNN, whereas the generation of temporal features is facilitated by GRU. These two layers of the learning paradigms are synthesized with self-attention maps to yield more accurate optimal features, even in low Signal-to-Noise Ratio (SNR) settings. Performance metrics were computed and juxtaposed with other deep learning models in a comprehensive evaluation, which was executed utilizing GNURADIO and the Raspberry Pi Model 4. The proposed methodology demonstrates superior sensing capabilities at various noise levels and modulation techniques, as evidenced by experimental results, when compared to antecedent deep learning models. As an avenue for future inquiry, the proposed study should concentrate on the enhancement of spectrum sensing methodologies that are compatible with 5G and Internet of Things (IoT) ecosystems.

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