Cognitive Radio Spectrum Sensing by a Hybrid Approach using CNN1D and Bi-GRU

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Abstract: In the proposed system of diapason in cognitive radios of the 5G network, deep literacy algorithms play a pivotal part in prognosticating different radio signal conditions. There are different algorithms used in the being that that are n't enough to identify different conditions of networks, as they've veritably low delicacy to identify different radio signals. In the being point birth ways are employed for cognitive radio diapason analysis. In this operation ‘ Radio ML 2018.01 A’ dataset is used. The given data set has applicable different types of radio signals with different modulation. In the being work, the author has used deep literacy algorithm CNN1D with different layers powerhouse subcaste, ReLU subcaste, maximum pooling subcaste, etc. It's observed that CNN- 1D is performing far better than pre trained algorithms similar as DenseNet and VGG. The data set contains a AWGN in type cumulative wide question noise. The performance of cnn 1D in this operation bidirectional gru is enforced which will optimize the point selection and contributes in perfecting the delicacy of diapason analysis in cognitive networks.

***Keywords* :** AWGN, Cognitive Radio, RadioML, CNN1d, Hybrid Algorithm.

I. INTRODUCTION

Exploration indicates that demand for radio frequence diapason has endured enormous increases. Traditional fixed diapason allocation fails to work effectively as unused diapason bands are unutilized during specific ages indeed though population operation of engaged diapason rises continuously. The Cognitive Radio technology gives a smart approach to address this issue. Using this system unlicensed druggies gain unused diapason automatically yet without causing detriment to certified systems. The primary operation of a CR system depends on diapason seeing to find vacant diapason ranges between licensed and unlicensed frequentness.

The three main diapason discovery ways which include energy discovery and matched filtering and cyclostationary point discovery are standard procedures for these operations. Accurate operation of these styles becomes largely grueling due to low signal- to- noise rate(SNR) along with high environmental noise situations. These styles need signal specifications information for proper prosecution although this information could be unapproachable in certain situations. The present diapason seeing styles need innovative advancement to descry signals more effectively in wireless dynamic conditions that operate withoutpre-defined specific features.

exploration studies demonstrate deep literacy serves as an advanced problem-working system throughout different sectors including wireless communication. RNNs and CNNs have proven their capability to find retired data patterns within undressed input signals while bypassing the demand for mortal- made point birth tools. Through deep literacy technology diapason seeing systems come more effective in detecting radio signals under varying conditions because of their automatic signal point recognition capacities.

Cortical signal bracket in cognitive radio networks depends on deep literacy diapason seeing armature with CNN1D along with ReLU and maximum pooling layers and powerhouse layers paired with sigmoid activation. The signals from multiple radio types of RadioML 2018.01 A suffer training in conditions that include AWGN(cumulative white Gaussian noise). The new model obtains superior issues through its use of a CNN1D network integrated with a Bidirectional Gated intermittent Unit(BiGRU). Through this concerted structure the system gathers spatial and temporal network features that produce better delicacy at advanced robustness situations.

Intelligent diapason seeing technology needs to be effective to enable the deployment of 5G wireless networks and unborn wireless networks from IoT to 6G. Deep literacy meets complicated terrain work conditions through its combination of inflexibility and learning implicit and adaptable features. The advancement of deep literacy mongrel infrastructures produces superior performance results compared to conventional ways since they establish paths for coming- generation wireless networks to reach effective diapason application.

II. LITERATURE SURVEY

1. Haykin (2005) established Cognitive Radio (CR) as a brain-powered wireless quantity that learns change automatically when environmental elements transform. The beginning of his research produced spectrum sensing as an essential feature to support dynamic spectrum access in CR systems. Standard sensing methods showed failure during uncertain and noisy conditions which led researchers to develop advanced intelligent detection methods for accurate spectrum measurement according to Haykin.

2. A detailed review of spectrum sensing schemes appeared in the Yucek and Arslan 2009 publication focusing on analyzing the distinctions between the various sensing methods such as energy detection along with matched filtering and cyclostationary detection. The authors evaluated multiple detection methods by showing direct links between their operational complexity and their functional outcomes and sensed measurement results. Deep learning techniques prove better alternatives to traditional methods because those methods give unreliable results in environments with dynamic conditions and low signal-to-noise ratios according to their findings.

3. Through their study in 2017 O’Shea and Clancy explored wireless communication automatic modulation recognition functions by utilizing Deep Learning techniques through Convolutional Neural Networks (CNNs). CNN neural networks surpassed traditional methods because they

found important signal elements from uninhibited measurement inputs. The resulting research enabled scientists to create a modern method for using deep learning models in cognitive radio spectrum sensing together with signal classification applications.

4. A deep reinforcement learning framework described by Rajendran et al. (2018) allows cognitive radios to find optimal channel access methods by interacting with their real-time environment. Through their dynamic system, the authors achieve performance improvements by adopting time-based adaptations instead of traditional rule-based methodologies. Spectrum sensing evolved into intelligent decision-making after transforming because reinforcement learning provided adaptable capabilities while deep learning added predictive abilities.

5. Ghanem et al. (2019) developed CNN technology to perform fast wideband spectrum sensing by monitoring large frequency blocks. Deep learning technology found success in spectrum band discovery through flawed and noisy inputs and produced reduced power and measurement duration requirements. CNNs delivered practical success in cognitive radio applications because they tested successfully for operational challenges.

6. The authors of Yin et al. (2020) established Deep Belief Networks (DBNs) as a spectrum state prediction system to achieve better generalization abilities alongside more robust learning compared to traditional learning models. Depth Belief Networks function effectively to model spectrum usage temporal dependencies which proves they work best for noisy wireless dynamic environments. New valuable advances were added to deep learning architecture research for spectrum sensing through this investigation.

7. A real-time spectrum sensing model emerged from the joint work of Xu et al. (2020), who united CNNs and LSTM networks because of their complementary nature. The authors created a wireless signal feature extraction model from space and order through an LSTM-CNN combination, which enhanced performance in complex conditions. The authors demonstrated a technique for building advanced spectrum sensing frameworks by joining different deep learning methodologies together.

III. Proposed Method

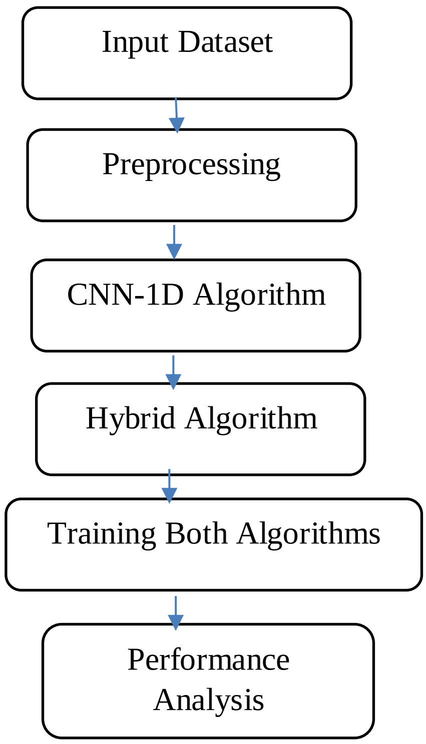

Fig. Block diagram of proposed method

The system starts by loading the RadioML2018.01A dataset, which includes various wireless signal samples labeled by modulation type and SNR levels. To prepare the data for model training, it goes through preprocessing steps such as normalization to scale the signal values and label encoding to convert class labels into a format that deep learning models can understand. After preprocessing, the dataset is split into training and testing sets to enable performance evaluation.

Next, two deep learning models are developed. The first is a CNN1D model designed to learn spatial patterns in the signal data. The second is a hybrid model that combines CNN1D with a Bidirectional GRU, which helps capture both spatial and sequential characteristics of the signals. Both models are trained on the same dataset, and their performance is tested across a range of SNR levels to see how well they perform under different noise conditions.

Finally, the models are evaluated using accuracy and confusion matrices. Visualizations such as graphs and performance plots are used to compare results. The hybrid CNN1D+BiGRU model generally shows better accuracy, making it a strong candidate for reliable spectrum sensing in cognitive radio systems.

Deep learning algorithm is used in 5G cognitive radio networks for spectrum sensing to identify diverse conditions of radio signals region of cognitive radio. In the existing different feature extraction techniques has been used for cognitive radio network analysis But these techniques are not up to the mark for spectrum sensing in cognitive radio of 5G.

There are different relevant types of modulation techniques has been utilized in this application to perform the analysis using hybrid deep learning algorithm which uses CNN1-D and Bi-GRU. To test algorithm performance author has used 'Radio ML 2018.01A' dataset which contains 11 different types of modulation or radio signals.

In existing work author [1] has used various layers from deep learning algorithm such as CNN1D, dropout, sigmoid, RELU and MAXPOOL1D layer. Propose architecture with above different layers are giving highest performance compare to other pre-trained algorithms such as VGG and DENSENET. To get best algorithm performance author has used dataset with additive white Gaussian noise (AWGN).

In propose algorithm author has used different layers from deep learning family to get best performance but not used any hybridization layer to further enhance accuracy. So as extension work we have enhance propose algorithm with extra algorithm called Bi-directional GRU which will optimize training features from both ends of the layer to get more optimize features. Collected optimize features can help algorithm in improving accuracy.

III. Results Analysis

Proposed method results are as shown in the below figure,

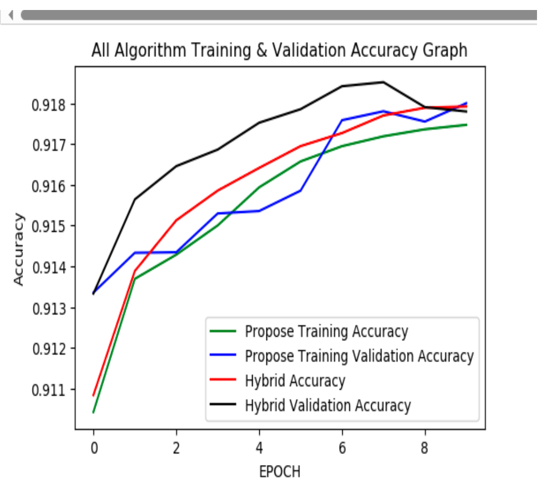

Fig.3.1 Accuracy Graph for existing and Proposed Method

In the above figure, accuracy, of proposed and existing algorithms are shown with training and training validation accuracy. From the above graph it is observed that accuracy of proposed hybrid algorithm is increasing with highest rate compared to the cnn algorithm. It means that proposed algorithm has superior performance compared to the state of Art Existing algorithms cnn algorithm and pre trained algorithms.

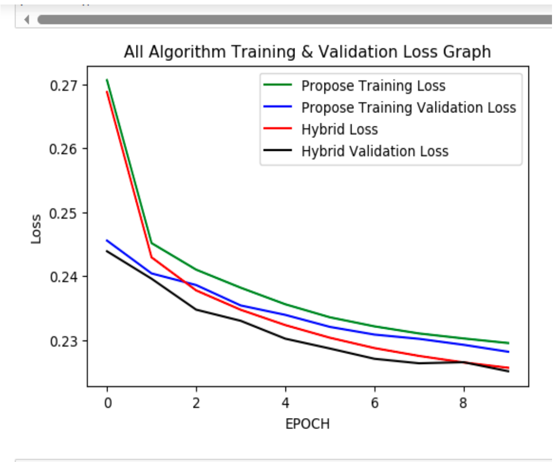

Fig.3.2 All algorithm training and validation loss graph

In the proposed algorithm, it is observed that training loss and validation loss are shown for both the proposed and existing algorithms. From the graph, it is observed that both training and validation loss are decreasing with the highest rate for the proposed algorithm compared to the existing algorithm, CNN. Hence, we can say that proposed hybrid algorithm has better spectrum analysis compared to the existing algorithm.

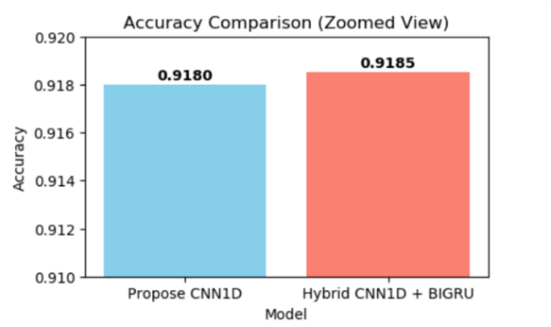

Fig.3.3 Accuracy Comparison Graph

In the above graph it is observed that the bar plot is plotted for both existing and proposed method. This graph represents that hybrid algorithm is superior compared to the state-of-the-art CNN algorithm.

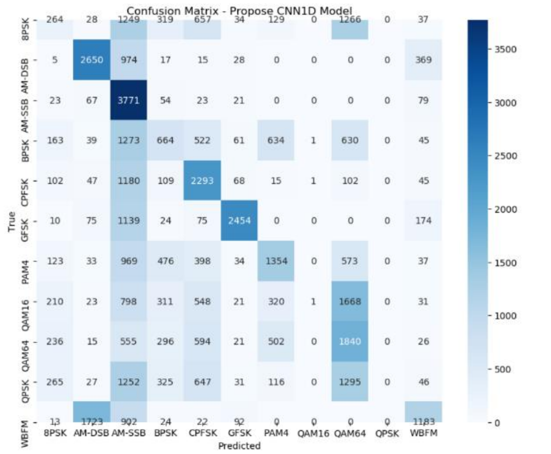

Fig 3.4 Confusion Matrix for CNN1D

In the above figure it shows how well the model differentiates between various modulation classes. Each diagonal value indicates correct predictions, while off-diagonal values point to misclassifications.

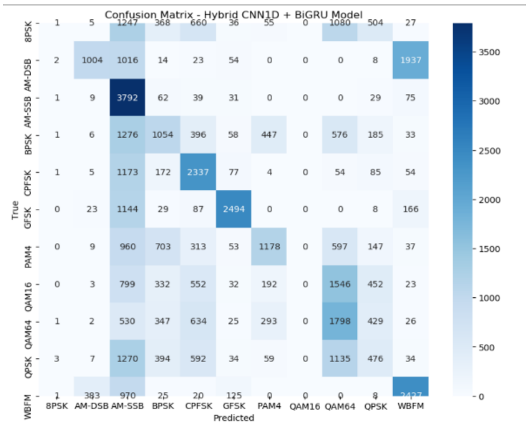

Fig 3.5 Confusion Matrix for Hybrid Model

This matrix presents the classification performance of the hybrid model across all modulation types. A more concentrated diagonal line compared to the CNN1D model reflects improved class-specific accuracy.

Conclusion

The proposed application is successfully designed using a hybrid algorithm, which is performing superior compared to the existing algorithm. CNN-1D. In this application, Bi-directional GRU (Bi-GRU) is used for effective spectrum sensing in cognitive radio networks. The proposed model uses additive wide gaussian noise channel, which is a noisy channel utilized for real time transmission in software. The same channel is utilized for both algorithms. And at the last, it is observed that a hybrid algorithm performs superior compared to the existing algorithm in both loss calculations as well as the accuracy calculations. Additive White Gaussian Noise (AWGN) is tested using the RadioML 2018.01A dataset by both algorithms CNN and hybrid algorithm.

As a hybrid algorithm is performing better compared to the traditional algorithms, this hybrid algorithm can be used for spectrum sensing in 5G cognitive radio networks with high accuracy.

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