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Deep Learning based Spectrum Sensing for data transmission in WSN

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Abstract:

This article discusses DL-based Spectrum Sensing (SS) in Cognitive radio employing CNN-BIGRU networks for efficient data transfer. Cognitive radio is an extremely important issue in wireless communication. Radio frequency spectrum scarcity exists in wireless communication owing to the development of digital technologies. SS is critical to successfully exploiting spectrum resources. The complexity and efficiency of allocation are reduced when using traditional SS procedures. If the main user is not present, resources may be properly used for the secondary user by employing DL-based SS. The CNN-BIGRU network discussed in this article can be used for effective data transfer. Good precision can be achieved by employing this model. In addition, low SNR signals can be successfully classified and provide information on whether the channel is idle or busy.

I. Introduction

In the dynamic and interconnected world of wireless communication, the efficient utilization of the radio frequency spectrum has become more important. Spectrum management systems must now be more sophisticated and adaptable due to the limited availability of spectrum resources and the increasing growth of wireless devices and applications. One potential remedy for these issues is SS, a crucial element of Cognitive Radio (CR) technology[1]. In order to identify underutilized or underused frequency bands, often known as spectrum holes or white spaces, SS is used to detect and evaluate the spectrum's occupancy state. By automatically detecting numerous spectral options, optimizing spectrum use, and minimizing interference issues, cognitive radio systems may dynamically adjust their communication quality and quickly migrate to open bands. Traditional static spectrum allocation techniques, which designate certain services or license holders to a specific frequency band, haven't lived up to expectations. Wide areas of the spectrum are often empty, even while other parts of it are in use. SS attempts to lessen these inefficiencies by using Dynamic Spectrum Access (DSA), which permits more access to vacant or lightly occupied spectrum by opportunistic users while ensuring that big users (licensed users) are not adversely affected[2]. Academicians, businesspeople, and regulatory agencies are all very interested in this cutting-edge approach to spectrum management. It has been regarded as a key facilitator for bringing the idea of a wireless ecosystem to life in the future, one that can efficiently use the supply of available spectrum and satisfy the continuously rising mobile demand. The usage of the radio frequency spectrum by wireless networks might be significantly altered by SS, a crucial component of cognitive radio. By allowing dynamic access to unoccupied airwaves, this technology may help a wireless society become better and more connected. Better communication reliability, more spectrum licensing alternatives, and more efficient spectrum use might result from this[3]. The following are the main goals of SS: Improved Spectrum Efficiency: Secondary users may take use of resources that exist by strategically using accessible spectrum, enhancing net effectiveness of spectrum. Spectrum coexistence: By quickly releasing frequencies whenever main subscribers require them, SS allows secondary users to cohabit alongside primary users. superior Quality of Service (QoS): Dynamic spectrum access enables superior QoS for both main and secondary users, improving network efficiency and user satisfaction [5]. SS helps to address the problem of spectrum scarcity by locating untapped or underused spectrum frequencies which can be exploited for secondary users. SS approaches use a number of strategies, such as energy detection, matched filtering, cyclostationary feature identification, and cooperative sensing, to accomplish these goals. The selection of approach relies on elements including signal qualities, noise circumstances, and the complexity of the deployment situation. Every strategy has benefits and limits [6-7].

II. Related Work

[8] et. al. discussed on identifying three designs that often provide classification precision in the range of approximately 90% at high SNR. These three architectures are a CLDNN, LSTM, and a ResNet. Lastly, sample training SNR values were determined, and it was discovered that training using data sets corresponding to only two SNR values—one at high SNR and another at low SNR in the range of -20 to 18 dB led to good precision for classification for a significant part of this spectrum. The subsequent studies will look at the best configuration of the approaches that have been described as well as novel techniques such employing denoising autoencoders. In a groundbreaking examination of the impact of the wireless channel on CNN-based fingerprinting techniques, [9] et al. used the 7TB experimental dataset. They provided a thorough, rigorous, quantitative assessment of how the wireless channel affects the accuracy of radio fingerprinting methods based on CNN[4]. The wireless channel significantly lowers classification accuracy, from 85% to 9% in the experimental dataset and from 30% to 17% in the DARPA dataset, respectively. Accuracy may be significantly (i.e., by 23%) boosted when I/Q data is equalized when there are more devices. a thorough investigation of the wireless channel's impact on the accuracy of CNN-based radio fingerprinting methods. a broad, open radio fingerprinting dataset amassed in a variety of environments and rich, varied channel circumstances. Fractional lower order statistics are employed in SS, claim [10] et al. It is demonstrated how the recommended strategy beats the conventional one in both Gaussian and non-Gaussian circumstances by a margin of 5.3%. The classifier can identify BPSK and QPSK signals with an accuracy of 40% to 99% and 27% to 98%, respectively, after channel correction. The misclassifications among M-QAMs generated lower classification likelihood for M-QAMs and the classifier as an entire

entity. In data-driven LSTM-based AMC model, [11] et al. CNN models tend to provide an additional 5–10% accuracy boost in small SNR circumstances (SNRs below 2dB), while LSTM models still continue to perform well in high SNR environments. The proposed model yields an average classification accuracy of close to 90% over a range of signal-to-noise ratio conditions from 0 dB to 20dB. With the use of efficient blind denoising methods, the low SNR performance of these SoA deep learning models may be significantly improved. Models which can deal any spread spectrum modulation imaginable should be used in future testing. Bayesian compressive sensing (BCS) model and cooperative spectral sensing technique were proposed by [12] et al. greater convergence rate with SNR values of 20 dB to 95% and 10 dB to 82%. It is necessary to prevent the impact of channel fading. The normal distribution of the outcome statistic and the ideal detection cutoff that fulfils a restriction on the likelihood of false-alarm were discovered by [13] et. al as they explored a unique goodness-of-fit detection strategy utilized for SS. for various with fixed SNR= 4 dB and M = 75. For = 2, DED and ED perform indistinguishably. It may be further enhanced by adding support for the scenario of numerous main users to the theoretical foundation. In their discussion of improved convolutional neural network (CNN)-AMC network (IC-AMCNet), [14] et al. discovered that the suggested method outperforms other methods in classifying the modulation of the transmitted signal in various SNR limitations. For various, for fixed SNR= 4 dB and M = 75. For = 2, DED and ED perform indistinguishably. Future improvements to the algorithms for DL, including changes to the number of layers as the dimension of every layer's filters, shall be taken into consideration. In their discussion of the nonparametric cyclic correlation estimator based on the multivariate (spatial) sign function, [15-16] et al. discovered that the spatial sign cyclic correlation detector's effectiveness for the complex Gaussian scenario is 61.7% of that of the cyclic correlation detector, resulting in a 1 dB performance loss for the DVB-T OFDM signal in AWGN noise. A robust Huber function-based cyclic detector has a significant increase in computational cost, which is a negative. [19] et al. spoke on how the amplitude distribution and density may be approximated by classical non-Gaussian noise, such as Middleton Class, and they discovered that it has a better approximation than Middleton Class A since it uses Edgeworth series expansion.Wireless communication and harmonics may be seen at 1.5, 2.5, and 6 GHz in the PSD collected at the 735 kV substation.We will also talk about the model's repeatability in comparison to experiments.

III. Design Methodology

In this paper CNN-BIRNN based SS method has been proposed. Where the input data can be considered from Radioml dataset. This dataset has been downloaded from (https://www.deepsig.ai/datasets) website. In the preprocessing stage, the gaussian noise sample has been added to the input data and labelling is given for both modulation signal and noise signal. The output of preprocessing stage is given to CNN and BIRNN network. The dataset contains various modulation signals both digital and analog which can be used to identify whether a Primary User signal is present in the channel or not. If the channel is idle it can be used for the Secondary to exploit the advantage out of it. And the user can generate their own dataset to analyse the spectrum sensing behaviour. In CNN network, throughout the learning phase, the neural network attempts to separate useful and prejudiced characteristics from its input dataset. The characteristics that a CNN learns to recognize rely on the architecture and depth of the network as well as the complexity and variety of the data used for training[17-18].

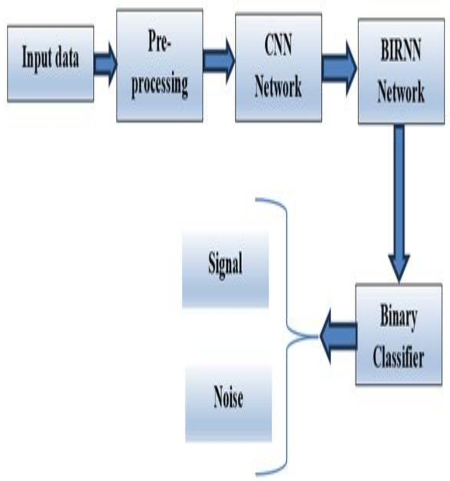

Fig. 1: Block diagram of proposed method

CNN considered have fixed number of units, maxpooling with pool size equal to two is considered. A sort of NN design known as a Bidirectional Gated Recurrent Unit (BiGRU) expands the idea of Bidirectional Recurrent Neural Networks (BiRNNs) by employing Gated Recurrent Units (GRUs) as the fundamental basic element. In contrast to standard recurrent neural networks (RNNs), BiGRUs can handle sequential input both forward and backward while resolving some of the vanishing gradient issues. The BIGRU output can be given fully connected layer with RELU activation can be considered. In this article this method is theoretically proposed. And this type of method may give better performance in wireless communication.

IV Conclusion

From the theoretical proposed algorithm, the hybrid algorithm CNN-BIRNN may yield better result. With the evolution of DL, SS may be performed in a more efficient manner when compared to conventional methods. As the DL methods may become alternative to conventional energy detection methods of performing SS. Conventional energy detection has many drawbacks, like complexity and less efficiency. Simulation may be performed on this hybrid model and it may give better performance compared to CNN architecture alone when considered. When BIRNN along with CNN is considered the performance and binary classification of signal (H_1) and Noise (H_0) may be done in a more appropriate way. And the theoretically proposed method may have better performance even at lower Signal to Noise ratios.

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