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DEEP LEARNING-BASED SPECTRUM SENSING FOR COGNITIVE RADIO APPLICATIONS

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ABSTRACT

Spectrum sensing is a critical function in cognitive radio networks, especially in emerging 5G communication systems, where efficient utilization of available spectrum is essential. Traditional feature extraction-based methods for signal classification often suffer from limited accuracy and poor adaptability in noisy environments. To overcome these limitations, this project proposes a deep learning-based approach for spectrum sensing to classify different radio signal modulations effectively. The proposed system utilizes the RadioML 2018.01A dataset, which contains multiple modulation types with varying noise conditions, including additive white Gaussian noise (AWGN). A deep learning architecture based on one-dimensional Convolutional Neural Networks (CNN1D) is implemented with layers such as ReLU activation, dropout, sigmoid, and max pooling to extract meaningful features from signal data. The model demonstrates strong classification performance compared to traditional and pre-trained models like VGG and DenseNet. To further enhance performance, an extension model combining CNN1D with Bidirectional Gated Recurrent Unit (Bi-GRU) is introduced.

This hybrid approach captures temporal dependencies from both forward and backward directions, improving feature extraction and classification accuracy. Experimental results show that the hybrid CNN1D + Bi-GRU model achieves higher accuracy (0.9185) compared to the base CNN1D model (0.918), along with reduced loss. This work highlights the effectiveness of deep learning and hybrid architectures in improving spectrum sensing accuracy, making it suitable for real-time cognitive radio and 5G communication applications.

Keywords : Cognitive Radio, Spectrum Sensing, Deep Learning, CNN1D, Bi-GRU, RadioML Dataset, Signal Classification, 5G Networks, AWGN, Modulation Recognition

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I. INTRODUCTION

The rapid growth of wireless communication systems and the increasing demand for high-speed data transmission have led to spectrum scarcity in modern networks. Cognitive Radio (CR) technology has emerged as an effective solution to address this issue by enabling dynamic spectrum access. Spectrum sensing is a key component of cognitive radio, allowing devices to detect available frequency bands and identify the presence of primary users. Accurate detection of radio signals is essential to avoid interference and ensure efficient spectrum utilization. Traditional spectrum sensing methods rely on feature extraction and statistical techniques, which often fail to perform well in low signal-to-noise ratio (SNR) environments and complex signal conditions.

With advancements in deep learning, new approaches have been developed to improve signal classification and spectrum sensing performance. Deep learning models, particularly Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have shown significant success in learning complex patterns from raw data. These models can automatically extract features from signal data without the need for manual feature engineering. CNN1D models are especially suitable for processing time-series signal data, while recurrent models such as GRU and LSTM can capture temporal dependencies within signals. These capabilities make deep learning a powerful tool for improving spectrum sensing accuracy in cognitive radio networks.

In this project, a deep learning-based framework is proposed for spectrum sensing using the RadioML 2018.01A dataset. The system employs a CNN1D architecture with multiple layers such as ReLU, dropout, and max pooling to classify different modulation types. Additionally, an enhanced hybrid model combining CNN1D with Bidirectional GRU (Bi-GRU) is introduced to improve performance. The models are trained and evaluated using standard metrics such as accuracy and loss. This approach aims to provide a robust and efficient solution for signal classification in cognitive radio and 5G communication systems.

II SURVEY OF RESEARCH

1. Traditional Spectrum Sensing Techniques

Early research in cognitive radio focused on traditional spectrum sensing techniques such as energy detection, matched filtering, and cyclostationary feature detection. These

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methods rely on statistical properties of signals to detect the presence of primary users. While energy detection is simple and computationally efficient, it performs poorly in low signal-to-noise ratio (SNR) conditions. Matched filtering provides better accuracy but requires prior knowledge of the signal, which is not always available. Cyclostationary methods can detect signals in noisy environments but are computationally complex. These limitations highlight the need for more advanced and adaptive approaches for spectrum sensing.

2. Machine Learning-Based Spectrum Sensing

Machine learning techniques have been introduced to improve the performance of spectrum sensing systems. Algorithms such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN) have been used to classify signals based on extracted features. These methods can handle non-linear patterns better than traditional techniques. However, they still rely on manual feature extraction, which can limit their effectiveness. Research indicates that the accuracy of machine learning models depends heavily on the quality of extracted features. This has led to the adoption of deep learning techniques that can automatically learn features from raw data.

3. Deep Learning for Signal Classification

Deep learning has significantly improved signal classification in cognitive radio networks. Convolutional Neural Networks (CNN) are widely used for extracting spatial features from signal data, while Recurrent Neural Networks (RNN) capture temporal dependencies. Studies show that CNN-based models outperform traditional machine learning methods in terms of accuracy and robustness. One-dimensional CNN (CNN1D) models are particularly effective for time-series data such as radio signals. These models eliminate the need for manual feature extraction and can adapt to complex signal patterns. This project utilizes CNN1D to improve spectrum sensing performance.

4. Hybrid Deep Learning Models

Recent research has focused on combining multiple deep learning architectures to enhance performance. Hybrid models such as CNN-LSTM and CNN-GRU have shown improved accuracy by leveraging both spatial and temporal features. These models can capture complex relationships within signal data, leading to better classification results. Bidirectional recurrent networks further enhance performance by processing data in both forward and backward directions. Studies

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indicate that hybrid models outperform single-model approaches in various signal classification tasks. This project extends the CNN1D model by integrating a Bidirectional GRU to achieve higher accuracy.

5. Impact of Noise in Spectrum Sensing

Noise is a major challenge in spectrum sensing, especially in real-world wireless environments. Additive White Gaussian Noise (AWGN) is commonly used in research to simulate noise conditions. Studies show that noise can significantly affect detection accuracy, making it difficult to distinguish between signals and interference. Deep learning models have demonstrated strong performance in handling noisy data due to their ability to learn robust features. This project uses the RadioML dataset with AWGN to evaluate model performance under realistic conditions.

6. Evaluation Metrics and Performance Analysis

Evaluating the performance of spectrum sensing models is essential to determine their effectiveness. Common metrics include accuracy, precision, recall, and loss values. Confusion matrices and graphical analysis are used to visualize model performance and identify misclassifications. Research emphasizes the importance of comparing multiple models to select the best-performing approach. In this project, both the proposed CNN1D model and the hybrid CNN1D + Bi-GRU model are evaluated using these metrics, with results showing improved performance for the hybrid model.

III. WORKING METHODOLOGY

The proposed system begins with data collection and preprocessing using the RadioML 2018.01A dataset, which contains multiple modulation types along with different noise levels such as Additive White Gaussian Noise (AWGN). The dataset is loaded and analyzed to identify modulation class labels and signal distributions. Preprocessing steps such as data normalization, shuffling, and encoding are applied to prepare the dataset for training. The data is then split into training and testing sets in an 80:20 ratio to ensure proper evaluation of model performance. This preprocessing stage helps in improving model accuracy and ensures that the data is suitable for deep learning algorithms.

In the next phase, the proposed deep learning model based on CNN1D architecture is implemented. The model includes layers such as convolutional layers for feature extraction, ReLU activation functions for non-linearity, max pooling layers for dimensionality reduction, and dropout layers to prevent overfitting. The model is trained using the training dataset, where it learns to classify different modulation signals. After training, the model is evaluated on the test dataset using performance metrics such as accuracy and loss. To enhance performance, a hybrid model combining CNN1D with Bidirectional GRU (Bi-GRU) is developed. This hybrid model captures both spatial and temporal features, improving classification performance.

Finally, the trained models are used for spectrum sensing and signal classification. The system compares the performance of the proposed CNN1D model and the hybrid CNN1D + Bi-GRU model using graphical visualizations such as accuracy and loss curves. The hybrid model demonstrates higher accuracy and lower loss, indicating better performance. The system outputs the predicted modulation type for given input signals. By combining deep learning techniques and hybrid architectures, the proposed methodology provides an efficient and accurate solution for spectrum sensing in cognitive radio and 5G networks.

IV RESULTS EXPLANATIONS

In propose paper author employing deep Learning algorithm for spectrum sensing in Cognitive Radio 5G network to recognize or predict diverse Radio Signals. In the past features extraction based algorithm was utilized to identify different signals whose classification accuracy is not good enough. Deep Learning algorithm prove its performance in various fields such as image and various text classification.

Deep learning classification success ratio migrating author of his paper to employ deep learning algorithm for signal classification. To test algorithm performance author has used 'Radio ML 2018.01A' dataset which contains 11 different types of modulation or radio signals.

In propose work author 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).

Extension Concept

In propose algorithm author has used different layers from deep learning family to get best performance but not used any hybridization

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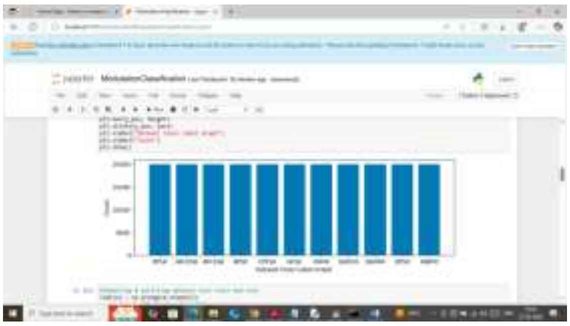
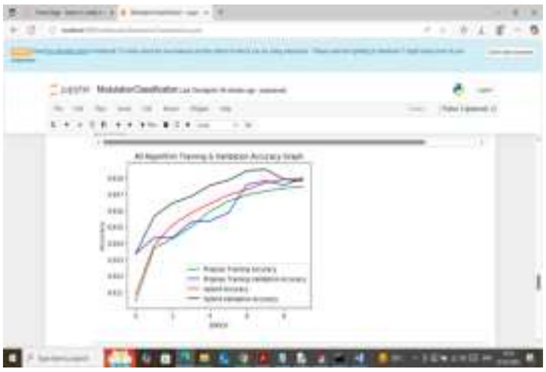
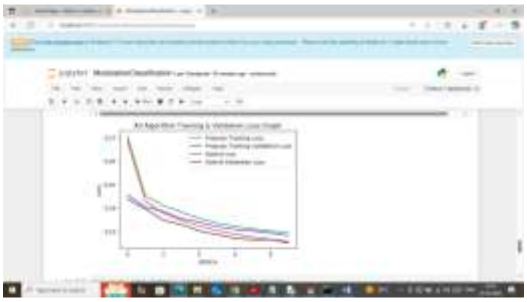
layer to further enhance accuracy. So as extension work we have enhance propose algorithm with extra algorithm called Bi-directional GRU which will optimize training features from both ends of the layer to get more optimize features. Collected optimize features can help algorithm in improving accuracy.



In above screen visualizing different modulation class labels graph where x-axis represents modulation or signal names and y-axis represents number of instances exists in that class label



In above screen visualizing propose and extension hybrid algorithm training and validation accuracy where green and blue line represents training and validation accuracy of propose model and then red and black line represents training and validation accuracy of extension model. In both algorithms can see extension got high accuracy. In above graph x-axis represents 'Training Epochs' and y-axis represents accuracy.



In above screen visualizing training and validation loss of both algorithms where extension got less loss

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In above screen visualizing overall accuracy of both algorithms where x-axis represents algorithm names and y-axis represents accuracy. In both algorithms extension got high accuracy.

V. CONCLUSION

The proposed deep learning-based spectrum sensing system for cognitive radio applications provides an efficient and accurate solution for classifying radio signal modulations in 5G networks. By utilizing the CNN1D architecture, the system successfully extracts meaningful features from raw signal data and achieves high classification accuracy even in noisy environments. The extension of the model using a hybrid CNN1D + Bidirectional GRU further enhances performance by capturing temporal dependencies from both directions, resulting in improved accuracy and reduced loss. Experimental results demonstrate that the hybrid model outperforms the base model, making it more suitable for real-time applications. The use of the RadioML dataset with AWGN ensures that the system is tested under realistic conditions. Overall, this project highlights the effectiveness of deep learning and hybrid architectures in spectrum sensing, contributing to better spectrum utilization and reliable communication in cognitive radio and next-generation wireless networks.

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