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Spectrum Sensing and Waveform Classification with Deep Learning

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Abstract: Over the years, engineers have gradually moved wireless communication systems upward into higher frequency bands, a trend driven by the need for wider bandwidth and larger coverage areas; radar, too, has long operated at these higher frequencies. Therefore, the spectrum of these two systems may overlap. In this research paper we designed a smart spectrum sensing system for radar and wireless communication system using deep convolutional neural network. We designed neural architecture for this purpose and labeling the data. Signal classification is equally important, because the growing number of modulation techniques makes it hard to tell at a glance whether a given burst is a wireless communication signal(smartphone call) or a whether radar ping. To tackle that challenge, the same neural architecture was adapted to recognize the waveform and modulation format of incoming signals, again relying on labeled synthetic data. MATLAB Simulink provided an accessible framework for generating, labeling, and pre-processing the training sets before they were fed into the network. For the spectrum-sensing task, traditional radar and wireless signals were synthesized in blocks, captured as time-series records, and then passed through the joint filter-classifier network. For waveform classification wigner ville distribution and convolutional neural network is used. Finally to the demonstrate and figure out the classification performance we used a confusion matrix, a confusion matrix compare true class values with predicted class values and gives the accurate classification values diagonally.
Key words*: *Spectrum sensing, Waveform classification, deep convolutionalneural network.

I. INTRODUCTION

In this paper we use deep learning [8] to sense unused spectrum bands and tell different radio waveforms apart, taking in signals from both radar sets and commercial wireless gear. Spectrum sensing looks at every slice of the radio frequency map to spot whether a licensed user is active, while waveform classification pinpoints the shape of the incoming signal and labels its modulation style.

Deep learning forms a heavy-lifting corner of machine learning; its stacked neural nets learn by passing data through many layers, and the deeper the stack, the more subtle patterns it can catch. Each layer scrubs the input with reshaped math, tweaking weights so the output matches the target a little better each time. Because of this layered structure, deep models tackle messy, high-dimensional problems where older methods stumble. Once the network is fed plenty of labeled examples- radar sweeps, smartphone calls, Wi Fi bursts- it learns to harvest meaningful features on its own, sparing engineers from painstaking hand-crafted rules. For our test bed, we will load the system with recordings from both radar and wireless signals and watch how well the model learns to tell them apart.

In addition to analyzing the received signal and determining its occupied bandwidth, the trained deep learning network will use a de ep convolution neural network (CNN) to classify the radar signal and the wireless communications waveform.

Recent years have seen a wide range of applications for deep learning (DL), including successful and forwardthinking research in sp eech recognition [7], network optimization [5], and natural language processing [9].

Deep learning (DL) initiatives and realworld implementation efforts are relatively small in the fields of wireless communication syst ems and signal processing.

In this study we model an intelligent receiver with deep learning to sense the received radio spectrum and classify the waveform and modulation type of the received signal.

A. Research Objectives

1) To differentiate between radar and wireless communication signals, accurately identifying each captured signal through deep learning.
2) To categorize the waveform and modulation types of radar and wireless communication signals using deep learning techniques.

3) To improve the accuracy of detecting primary users (PUs) within a specified frequency band. To ensure that spectrum sensing is resilient against noise and interference.
4) To attain a high level of accuracy in the classification of various waveform types.
5) To minimize the chances of misclassification and missed detections.

II. LITERATURE REVIEW

As machine learning has progressed, numerous researchers have explored spectrum sensing and waveform classification through its application.

For instance, the research cited in reference [15] implemented various spectrum sensing methodologies utilizing "support vector ma chines" and Gaussian mixture models, where the author considered the energy of the received signals as an input feature. Some scho lars have pursued the integration of distinct detection methods (such as energy detection and cyclostationary feature detection) to en hance spectrum sensing via machine learning, significantly boosting spectral sensing efficiency. Certain sensing methods require int ricate implementation and a comprehensive understanding of the primary user's signal, as noted in reference [2]. Nonetheless, in thei r investigations, they encountered issues like hidden terminal problems or noise uncertainty that impact sensing accuracy and detecti on efficacy.

This research, however, is entirely focused on "deep learning." Deep learning possesses the capability to manage vast datasets, analy ze information with precision, and address hidden terminal issues within wireless communication systems. Although there exists a s ubstantial body of literature concerning spectrum sensing and waveform classification in communication systems and radar, empiric al research employing deep learning is quite limited. Nevertheless, with deep learning, researchers have primarily concentrated on d etecting and analyzing specific signals for particular tasks; this work, in contrast, addresses signal detection and analysis in a general sense.

III. RESEARCH METHODOLOGY

This study consists of two tasks, the first task is to sense the received signal spectrum and the second task is to classify the waveform and modulation type of the received signal. This work was carried out in the MATLAB Simulink environment.

A. Spectrum Sensing

We considered an airport surveillance radar, which used a reflector antenna having gain 32.8dB and operating frequency is set to be 2.8GHz with 2500watt transmit power. In the surrounding area of the airport radar, LTE signal and 5G signal are also present there, so we defined these signals using LTE and 5G toolbox. There are many scatterers in the surrounding area which produces difficulties for operation of propagation channels. In this study we assumed thirty (30) scatterers in the surrounding area.

1) Generate Training Data

For generating the training data, in Simulink we defined the data folders and names of class for Radar data, 5G data, Long Term Evaluation (LTE) data and noise. We generated spectrogram to observe the waveform type and the bandwidth of the signals.

2) Loading the Trained Data

We used the function "imageDatastore" for loading the 'training data' with the 'spectrograph' of radar and others inputs like (5G and LTE). This function is used to load the images from the drive. (Note: 'Spectrogram images' are in '.png' format.) Now for labeling the bandwidth of every signal, we used the function "pixelLabelDatastore" for loading 'spectrograph' image_pixel data (Note: image_pixel are stored in '.hdf' format). Each pixel in the "spectrogram" images is labeled as one of the categories Radar, 5G, Long Term Evolution and Noise.

Analyzing Datasets

To observe the division of class_labels inside the trained data. We used the function "countEachLabel" for counting the numbers of pixel of Class_label, and we plot this pixel_count by class which is shown in figure 1.

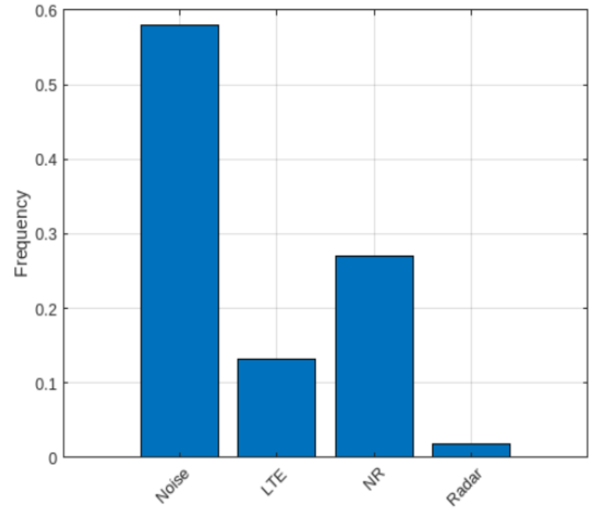

Figure 1 Pixel Count by Class

Split Validation and Training

We used the function "helperSpecSensePartitionData" for dividing the pixel data and images into two parts one part (80%) is for training and second part (20%) is for validation the data.

3) *Training the NeuralNetwork*

To design the Neural-network, we used the function "deeplabv3plusLayers". For the based network we select "resnet50" and then we defined the numbers of pixel used to define the time and frequency axes (input image size) with numbers of classes. To select the training option, we configured the training by running the function "trainingoption" which describe SGDM (stochasticGradientDecent with Momentum) algorithm. For the enhancing of training option we used experiment manager of deep learning toolbox for achieving best performance from the network. Below figure 2 shows the overall training progress.

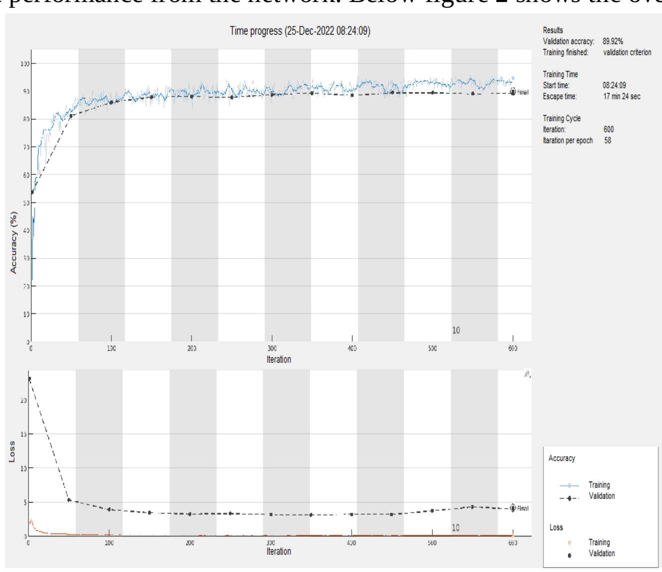

Figure2 Training Accuracy and Loss

4) *Test with Input Signal*

We used the input signal that has radar, LTE and 5G signal and test the signal recognition performance. We used the function "semanticsseg" for the tested dataset to achieve the pixels of the images. Then we used the function "eveluatesSemanticsSegnmentations" to get the metrices for evaluating the quality of the results. The flowing figure 3 show the "normalize confusion matrix" for tested data.

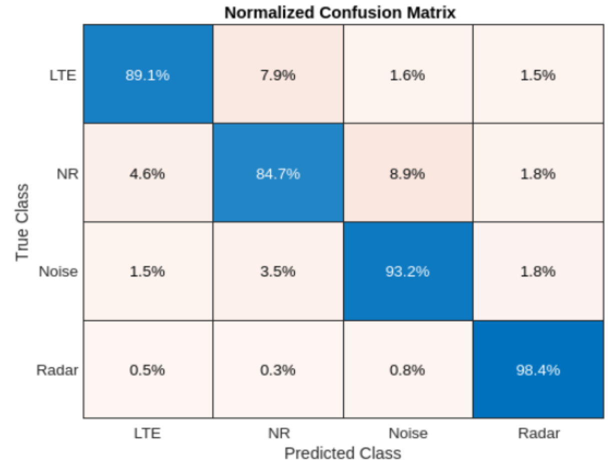

Figure 3 Normalize Confusion Matrix Plot

5) Identifying the Signal

For identification of the LTE, 5G and radar signals. The received spectrum, the true signal labels and the estimated labels clearly show that the radar signal is picked out from the input signal as shown in figure 4 below.

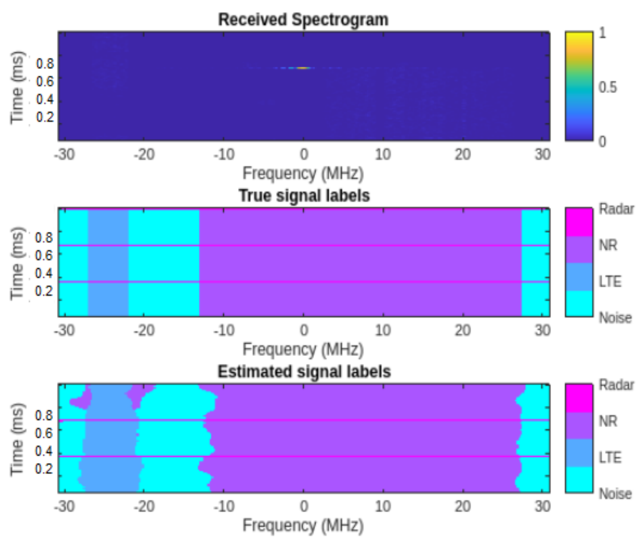

Figure 4 Identification of the received signal.

B. Waveform Classification

For waveform classification we used deep convolution neural network and Wigner Ville distribution. Wigner Ville distribution is used in signal processing for analysis of time-frequency representation of any signal.

1) Generating Waveforms for Radar

In this study we took three types of waveform rectangular wave, linear frequency modulation and barkerCode waveform for radar signal. We generated "3000" signals in this study for each signal (modulation type) we took sample rate of "100MHz". We used the following codes for each waveform in Simulink.

For rectangular pulse we used "phased.RectangularWaveform".

For linear frequency modulation (LFM) we used "phased.LinearFMWaveform".

For barker code we used "phased.PhaseCodedWaveform".

All the signals are randomly generated and used the function “awgn” to debilitate the signal with white gaussian noise to make it more realistic. Figure 5 shows the Fourier transform of Linear frequency modulation (LFM) waveforms which indicate differences in generated dataset.

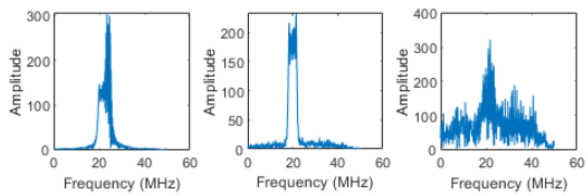

Figure 5 Linear Frequency Modulation Waveforms

2) Wigner Ville Distribution WVD (Extracting Features)

For each modulation we used the function “wvd” for finding Wigner Ville distribution (WVD) “smooth pseudo” which is shown in figure 6. WVD represents the original input data in the “time-frequency” view, it is useful for extracting features of the signals which is very helpful in classification and identification of the modulation.

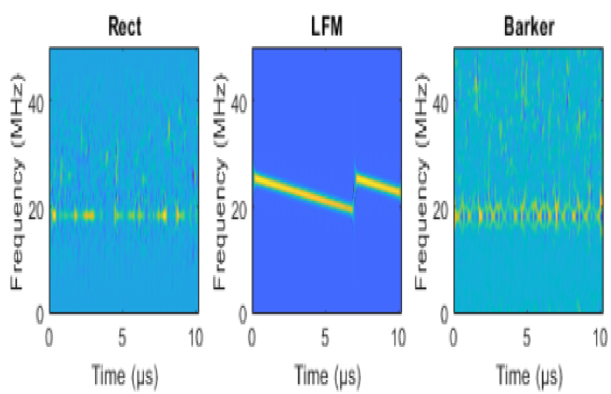

Figure 6 WVD Plot for Radar Wavefoms

We found out the WVD “smoothed pseudo” for each signal and reducing the sample rate of each signal’s output to matrix of size “227” rows and columns. And store the result as a image format file(e.g “.png”. For each signal we created folders and labels with names for specification of modulation type of each signal. This data is utilized for training the deep convolutional neural network.

We used the function “splitEachLabels” for splitting the “imagesDataStores” in three parts one part (80%) is used for training the network, second part (10%) is used for testing the datasets and third part (10%) is used for validation the datasets.

3) Deep Learning Network (Setup)

We used the function “SqueezesNet” before training of the deep learning neural network. “SqueezesNet” is used for image classification and configure the neural network. As the image size is {227 by 227 by 3}. We used the function “readTFDForSqueezesNet” for converting the 2D time-frequency distribution to “RBG” file(image). By default, the “SqueezesNet” classify one thousand categories.

4) Training the DNN

We used the code “trainNetwork” for training the created convolution neural network. The figure 7 show the “training accuracy plot.” Of all the iterations.

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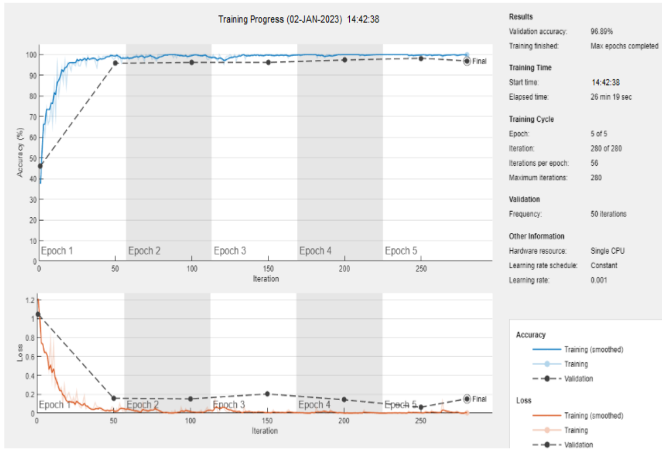

Figure 7 Training Accuracy Plot

5) Access Result for Radar Waveforms

We used the function command "classify" for classification of testing data of the training network. For visualizing the classification results we used the confusion matrix. We used the function "confusionschat" for this purpose. The result of the confusion matrix is shown in figure 8 which shows that the input radar waveform are recognized by the network.

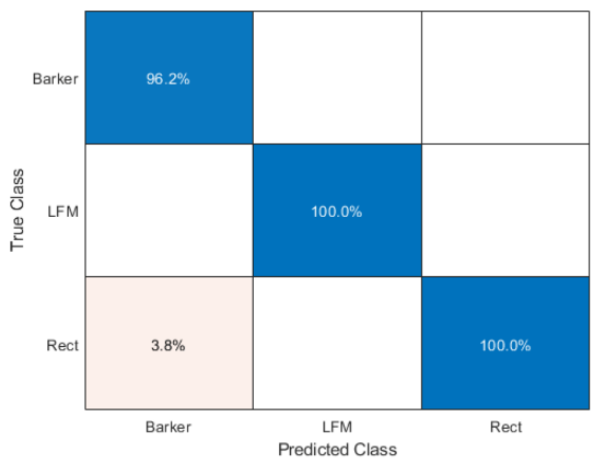

Figure 8 Confusion matrix of Radar waveform

6) Generating wireless comm waveforms

We generated 5 types of modulations waveforms for wireless communication systems, which are given below, G-FSK, C P FSK, B - FM, S S B - AM, and D S B - AM

For generating these communication waveform, we used the code "helperGenerateCommWaveforms". This helper code took data from MATLAB "communication Toolbox". We used Wigner Ville Distribution (WVD) for extracting features of the waveform therefore only subset of AM and FM types is used.

For each modulation type we used the Wigner Ville Distribution (WVD) function to visualize the waveform and extract time frequency features.

For finding the "smoothed pseudo" "WVD" for the each waveform, we used the function "helperGeneratesTFDfile". Then for managing the modulation types images files we created a datastore object. Again, we divide all input data into three parts,

Training the dataset,Validation the datasets, And testing dataset.

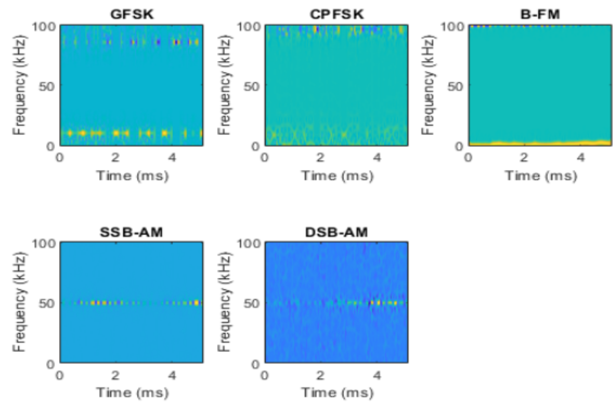

Figure 9 WVD Plot for Communication Waveform

7) Training the Deep Neural Network

We used all the eight modulation types, three modulation types of radar and five modulation types of wireless communication system for classification. Then we use the function command “trainNetwork” for training the convolutional neural network. The training accuracy is about 96%, and the training process took time about 144 minutes. We have done 1280 iterations and 128 iterations per epoch. The overall training progress is shown in figure 10.

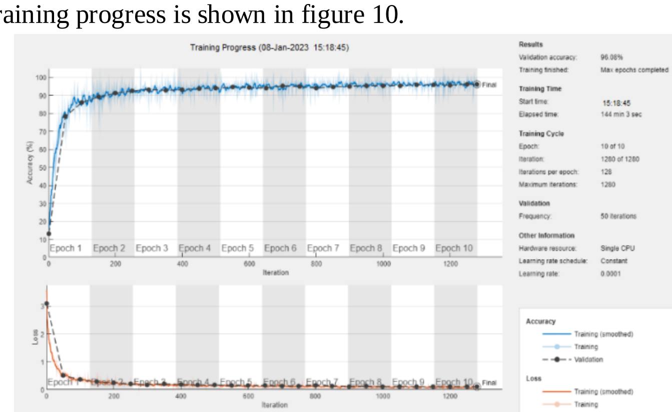

Figure 10 Training Accuracy Plot

8) Access Result for all Waveform

After training the CNN we used the function command “classify” for classification of the signal. Again, we used the “confusionchart” for visualization of the results, the confusion chart is shown in figure 11 which indicates that all the eight modulation types are correctly classified.

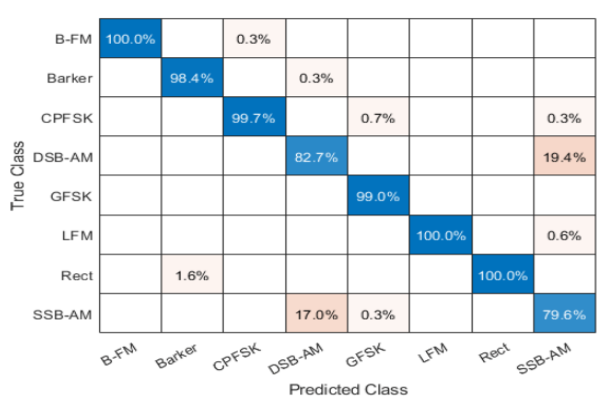

Figure 11 Confusion chart for the signal

IV. RESULTS AND DISCUSSION

In this research study deep learning (convolutional neural network) has been successfully applied to Spectrum sensing and Waveform classification. For spectrum sensing deep learning (Convolutional neural networks) is used to learned keen features from the received signal and make predictions related to the presence or absence of the primary users.

A. Spectrum sensing

Consider figure 3 and figure 4 the results show that using deep learning Convolutional Neural Networks for spectrum sensing of signals has significantly improved the detection accuracy as compared to traditional methods like energy detection and matched filter detection. Figure 3 show a confusion matrix the column correspond to true class values, these true class values are the actual values and the row indicate predicted class values, these predicted class values are predicted by machine learning algorithm. In confusion matrix the diagonal values show how many times the samples are correctly classified, figure 3 shows that radar signal values are classified 99.2%, NR values are 80.5% and LTE values are 93.8% correctly classified.

Figure 4 visualize the received signal, this is frequency vs time graph, the frequency is on x-axis and the time is on y-axis, there are three graph in figure 4, the first graph is the received signal, the graph shows the true signal and the third graph shows the estimated signal. In this graph the pink color shows the radar signal, purple color shows LTE, sky blue color shows NR signal and sea blue color indicates the noise in the signal. Therefore the network correct identified the radar, NR and LTE signal correctly from the received spectrum.

B. Waveform Classification

Using WVD(Wigner VilleDistribution) and CNN(convolution neural network) combined is a power approach for analyzation and classification of signals. Wigner ville distribution transform the time domain signals to time frequency representation that is suitable for deep convolution neural network. Deep convolution neural network automatically extract the features from time frequency representation. We took three radar waveform rectangular wave, LFM and BarkerCode and five types of communication waveform GFSK, CPFSK, B-FM, DSB-AM, SSB-AM.

Figure 5 shows the radar signal in frequency domain we used Wigner ville distribution (WVD) to transform the signals time frequency domain, which is shown in figure 6. then we trained the deep neural network with the data set and got result which is shown in figure 8. Figure is confusion matrix of radar waveform the diagonal of this matrix shows the correctly classified waveform of radar signal, the rectangular waveform is classified 100%, the linear frequency modulation form is classified 99.7% correctly and 0.3% mixed rectangular waveform and the barker code is classified 98.7% correctly and 1.3% mixed with rectangular.

Figure 9 shows the Wigner ville distribution of communication signals, we trained the deep neural network with previously radar signal combined with the communication signal. Finally the network classified all the 8 types of waveform correctly which is shown in figure 11. Figure 11 shows a confusion chat for all communication waveform and radar waveform. Diagonal of this matrix shows that the all 8 types of modulation are correctly classified.

V. RESEARCH CONTRIBUTION

In this study we design a smart receiver model using deep convolutional neural network that has the ability to sense the received spectrum and identify the signal as well as do the classification of the waveform. The key contribution of the study is the system perform the spectrum sensing and signal identification at low SNR value and do classication of waveform with high accuracy. Many researchwe work in this field but their work is limited to a specific task only, however this research focus the signal detection and waveform classification in general sense.

VI. FUTURE RECOMMENDATIONS

There are various important areas to consider for future study in spectrum sensing and waveform classification that leverages deep learning to address existing challenges and identify new paths of inquiry. Here are some suggestions for moving the field forward.

- It is important to more investigate the deep learning model for 6G network specific challenges, like high frequency communication and massive MIMO.
- Need Research for the multi-task learning framework optimizing spectrum sensing and waveform classification together.
- Robustness to Dynamic Environments Create deep learning algorithms for robustness under dynamic and adversarial conditions.

- Dataset Development and Benchmarking

The researcher can create large-scale, diverse and publicly available datasets for spectrum sensing and waveform classification with deep learning.

VII. CONCLUSION

Spectrum sensing and waveform classification are essential elements of contemporary wireless communication systems, facilitating effective spectrum use and reliable signal recognition. Utilizing deep learning methods, we have shown considerable progress in these fields.

Deep learning architectures, like convolutional neural networks (CNNs), have demonstrated exceptional abilities in identifying intricate patterns within raw signal data, surpassing conventional techniques in accuracy and flexibility.

Incorporating deep learning into spectrum sensing enhances the accuracy of detecting spectrum gaps and primary user signals, even in environments with low signal-to-noise ratio (SNR). Likewise, in waveform classification, deep learning models are proficient at recognizing and differentiating various modulation schemes.

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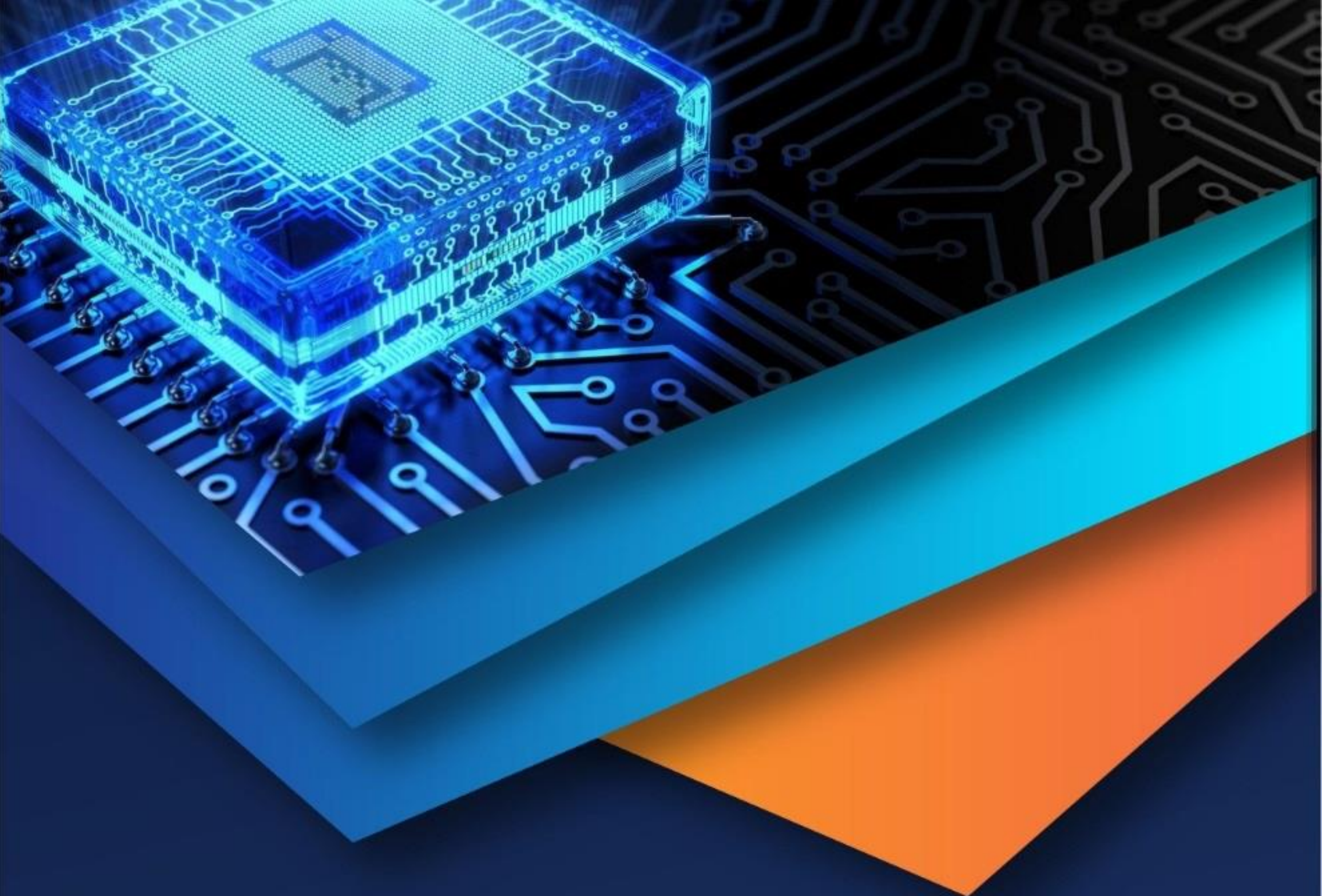

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