Specific Emitter Identification using Deep learning Models

By
Muhammad Montaha
(Registration No: 00000327401)

Supervisor
Dr. Muhammad Usman Akram

DEPARTMENT OF COMPUTER & SOFTWARE ENGINEERING
COLLEGE OF ELECTRICAL & MECHANICAL ENGINEERING
NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY
ISLAMABAD, PAKISTAN

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Signature : Usman

Name of Supervisor: **Dr Muhammad Usman Akram**

Date: 18-04-2024

Signature of HOD:
(Dr Usman Qamar)
Date: 18-04-2024

Signature of Dean: Rashid
(Brig Dr Nasir Rashid)
Date: 18 APR 2024

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Muhammad Montaha
(Registration No : 00000327401)

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Supervisor
Dr. Muhammad Usman Akram

DEPARTMENT OF COMPUTER & SOFTWARE ENGINEERING,
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NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY
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Dedicated to my parents, whose tremendous continuous support and endless prayers led me to this accomplishment.

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Abstract

In today's world, Specific emitter identification (SEI) has become crucial task in electronic warfare and signal intelligence that involves identifying a particular communication device by examining the unique radio frequency (RF) signals it emits. The ability to discriminate between different emitters is essential for ensuring the security and efficiency of communication networks, spectrum management, and electronic warfare operations. Existing emitter recognition methods often ignore the radio frequency (RF) fingerprint details carried by the waveforms which are primarily susceptible to a specific application scenario and radio environment and thus can be interfered with by unreliable RF features. It has been found that deep learning methods have demonstrated effectiveness in this task. This research introduces an innovative approach for Specific Emitter Identification (SEI) utilizing a Savitzky-Golay filter for denoising and a Stacked Multivariate Convolutional Neural Network (SMvCNN) architecture for classification. The inputs which are fed to Stacked Multivariate Convolutional Neural Network (SMvCNN) are time domain, frequency domain and phase of signals. By using this our proposed method surpasses conventional machine learning classifiers, achieving an impressive classification accuracy of 96% even under challenging conditions with a signal to noise ratio (SNR) of 5 dB. The integration of the Savitzky-Golay filter for noise reduction and the SMvCNN model demonstrates superior performance, underscoring its potential as a robust SEI technique in real-world scenarios.

Key Words: Savitzky-Golay filter, Time Domain, Frequency Domain, Radio Frequency, Machine Learning, Deep Learning, CNN Model, Signal-to-Noise Ratio (SNR).

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Chapter 1

Introduction

In recent years, wireless communication has developed and became significant part of our daily life [1]. The newly wireless technology aims to get wider coverage, large no of users and improve power consumption. With the increase of wireless technology there are many challenges associated with it. Especially its security due to the broadcast nature of the wireless channel as it is openly accessible to both legal and illegal users [2]. In comparison to wired communication, the open wireless environment makes communications more susceptible to attacks such as passive eavesdropping for data interception and active jamming causing disruptions to legitimate transmissions. Device Authentication is one of the methods to secure wireless communication. Some traditional methods, bit-level security mechanisms have been used to protect wireless networks. However, these techniques frequently have flaws. In recent years, a great deal of research has been done on radio frequency fingerprinting (RFF) [3]. The term RF fingerprint describe the variations in transmitters caused by manufacturing and debugging, This variation can be extracted from the signal received from the transmitter and is used to uniquely identify each wireless device. The extraction of the variation is known as RF fingerprint extraction. The method is also known as specific emitter identification [4] which aims to differentiate authorized transmitters users based on the unique characteristics of radio frequency signals at the physical layer. Figure 1.1 illustrates a standard framework for RF Fingerprinting (RFF). This framework serves the purpose of extracting the inherent characteristics or distinctive attributes from intercepted signals. In practical terms, it outlines the process by which relevant information is derived from the received RF signals, enabling subsequent analysis and identification.

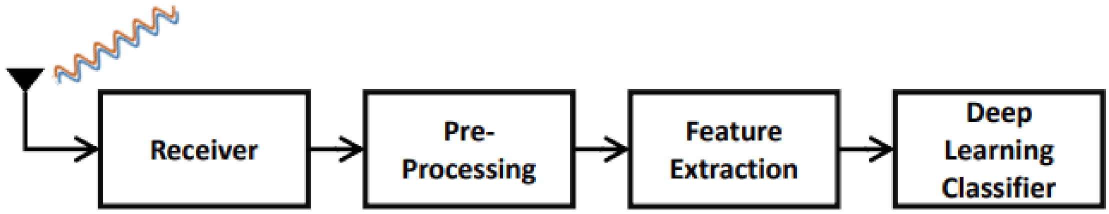

Figure 1.1: Basic Framework of RFF Extraction.

Only the legitimate users have given acces to use the network which improves the network security moderately. The SEI method has been implemented in variety of systems containing intrusion detection, satellite communication, IoT, radar and network security systems in 4G and 5G networks.

1.1 Motivation

As the wireless technology is getting advance day by day, the wireless security has become the topmost concern. Devices need to be recognized using both conventional and unconventional methods.The basic operating principle is that every electronic device is made up of many numerous nonlinear components. Since there is a certain amount of tolerance used during component manufacturing, which means that manufacturing errors cannot be avoided and this unique non linearity for each device distinguishes it from the others, just as humans have different thumb prints despite having the same name.The same approach is used here despite having the same make and type of transmitter, each device is different and unique due to its hardware components.

Specific emitter identification (SEI) is a technique of identifying a wireless transmitter based on its physical RF waveform. Although the name SEI may indicate the capacity to identify a unique ”fingerprint” for each particular wireless device, this is not always the case. SEI, on the other hand, has been demonstrated [4] to be beneficial for detecting larger kinds of devices. The commonly RF feature-based SEI technique generally consist of steps such as pre-processing, feature extraction and identification [5]. The pre-processing stage generally contains several operations like power normalization, target signal interception, filtering and so on [6], While the fundamental processes of SEI are feature extraction and identification. Prior to the advent of deep learning (DL), traditional SEI approaches generally used statistical techniques to create features, then followed by machine learning classifiers for identification. Although there are several drawbacks of RF features created by artificial knowledge like weak performances and the inability to deal with complicated and numerous wireless transmitters.

In last few years deep learning has proved to have powerful technique for data analysis [7],These DL-based SEI techniques, which have been shown to perform better than artificial hand crafted feature-based approaches, used deep neural networks to extract more robust and useful RF features from large historical RF signal samples.

1.2 Problem Statement

With the advance in wireless network technique its security becomes of paramount importance. Specific emitter identification distinguishes cradio emitters with the fingerprint features obtained from the received signal and this method has been widely used in military and civilian fields. SEI is generally labeled as a classification task. To identify any radio frequency transmitter, underlying nonlinear characteristics of hardware can be used as a unique ID for specific emitter identification. Deep learning-based techniques are getting popular to build smart and intelligent classifier in which manual signals feature extraction is not mandatory. The deep learning model takes the raw input to automatically finds the features which is then used for classification purposes.Therefore, the specific problem statement for the proposed research is ”To identify specific signal emitters using deep learning under low SNR ”.

1.3 Scope

Many SEI techniques based on manual hand crafted feature extraction have been developed recently, including IQ imbalance [8], power spectral density [9], Hilbert-Huang transform [10], etc. However, it has been established that they require manual feature engineering based on protocol and are highly dependent on the calibre of receiver hardware. Combining a data-driven convolutional neural network (CNN) with a steady-state RFF for SEI has drawn more interest in light of the impressive advancements in deep learning across numerous fields [11]. In contrast to the human feature extraction used in the SEI technique, the SEI approach built on deep learning often uses CNN model and input he original signal directly and associate the emitter without the need for manual hand crafted feature extraction. In essence, the deep learning-based SEI technique matches the input and output by developing non-linear functions, which is typically considered as an automated feature extraction framework to separate the emitter.

1.4 Aims and Objectives

The objectives of this research study are:

1. To design and develop a deep learning-based framework capable of using radio frequency (RF) fingerprint of signal to identify the individual emitter.
2. To get better emitter identification accuracy under low signal to noise ratio(SNR).
3. To enhance the security of various wireless communication systems.
4. Comprehensive evaluation of the proposed method is carried out using the most recent methods on real-world and open-source datasets.

1.5 Contribution

The contributions of this paper are summarized as follows:

1. We employed a distinctive approach with the Savitzky-Golay Filter (SGF) to capture the signal's envelope and extract samples representing the steady-state portion of the signal.

2. SMvEnN, a technique that combines stacked multivariate networks, was introduced to attain precise classification even in scenarios with low Signal-to-Noise Ratios (SNR).

3. Thorough assessment of the proposed approach is conducted by comparing it with the latest methods using both real-world and publicly available datasets.

1.6 Thesis Organization

The organization of the thesis is as follows:

- Chapter 2 presents the state-of-the-art side-channel attacks and their types.
- Chapter 3 comprehensive literature analysis of specific emitter identification with feature based approach and deep learning based approach
- Chapter 4 presents the proposed network in detail.
- Chapter 5 discuses the datasets, evaluation metrics and implementation detail. It also presents the comparison of our proposed network with already methods in terms of accuracy.
- Chapter 6 concludes the thesis and presents future directions along with major contributions of our research.

Chapter 2

Principles of Radio Frequency Fingerprinting

Radio frequency (RF) fingerprinting refers to the distinct set of characteristics and patterns present in the RF signals emitted by electronic devices. Devices like laptops, smartphones, and Internet of Things (IoT) devices emit RF signals when communicating with a network. Differences and defects in the hardware components of radio transmitters, such as errors in analog-to-digital converters, local oscillators, and power amplifiers, can be reflected in the propagated signals, creating a unique pattern known as an RF fingerprint. If developed, this RF fingerprint has the potential to allow the signal receiver to identify the transmitter by analyzing the characteristic of the propagated signal.

Typically, the RF fingerprinting process involves two main steps. Firstly, a database is established using the created fingerprints, where each fingerprint represents a unique identifier associated with a device or a specific category like model. Secondly, any fingerprint extracted from the device(s) in question is then compared to the database for the purpose of identification, essentially functioning as a pattern recognition system. In this identification system based on RF fingerprinting, the communication signals of devices are captured, undergo feature extraction, are stored in a database, and are subsequently compared to the database when new device signals are generated, facilitating the identification of devices or their respective classes.

2.1 Basics of RF Emission Characteristics

The fundamentals of radio frequency (RF) emission characteristics are essential to comprehending the core of RF fingerprinting. This section examines the essential characteristics and ideas that characterize the distinct radio frequency signatures that electronic devices emit.

2.1.1 Radio Frequency Signal Properties

2.1.1.1 Frequency

Frequency is a basic feature of RF transmissions that describes the pace at which a signal oscillates. Various electronic devices operate on particular frequency bands, and the device at which it transmit the signals or it recieves the signal at some frequency can be use as a discriminating feature. The frequency at which a device emits signals has a significant impact on its distinct RF signature. Variations in frequency can be use to identify many devices.

2.1.1.2 Amplitude

Amplitude indicate radio frequency signal strength or the power. The signal amplitude can be influenced by number of factors such as transmitter power or the distance from the receiver. Difference in amplitude can also help to distinguish RF fingerprints. The devices can be differentiated by analyzing the amplitude changes.

2.1.1.3 Phase

Relative position of a waveform in time refers to phase. Phase discrepancies in RF signals can arise from variances in signal propagation pathways, different antenna designs, or other specific aspects of devices. Phase information is used for signal arrangement and synchronization in communication devices. Analyzing phase differences can be used as differentiating powers of RF fingerprinting. Each device's RF signature is different due to its specific phase characteristics present in signal.

2.2 Signal Variability

The intrinsic differences and oscillations in radio frequency (RF) emissions can happen between electronic devices, even in same model and type, are usually stated as signal variability. Since signal variability is the root for differentiating the devices from one another, it is essential for RF fingerprinting. Following section will tell about the causes of signal fluctuation and its importance for RF fingerprinting.

2.2.1 Manufacturing Variations

The word "manufacturing variations" refers to difference in the construction process that give devices their unique characteristics. Difference in material quality, assembly techniques, and electronic devices tolerances often cause these discrepancies. It's difficult to create unique uniform RF fingerprinting models for same model devices due to manufacturing errors.

2.2.2 Aging Effects

Aging effects in the context of radio frequency (RF) emissions are the changes that occur in device components over time due to number of factors such as utilization, environment conditions, and wear and tear of devices. These effects that come from device changes can have an impact on the strength and characteristics of RF signals sent by devices, giving them a non lasting fingerprint. Considering these aging effects is critical for long-term distinctiveness of RF fingerprints.

2.3 Signal Processing Techniques

Radio frequency (RF) fingerprinting depends massively upon signal processing methods. These methods include analyzing and handling radio frequency signals in order to extract relevant features and find distinct patterns. This section inspects the various signal processing algorithms that are used in RF fingerprinting.

2.3.1 Spectrum Analysis

In radio frequency (RF) fingerprinting, spectrum analysis is a fundamental signal processing method. In order to find unique patterns and features, it requires analyzing the frequency components present in a RF signal. Studying the basic of spectrum analysis is the focus of this subsection.

2.3.1.1 Fourier Transform

A fourier transform is mathematical approach that breaks down a signal into its complex frequency components. It shows what frequencies that are present in the signal by providing a depiction of it in the frequency domain.

2.3.1.2 Spectrogram Analysis

A spectrogram is a figure that shows how a signal's frequency spectrum or it contents changes over time interval. It offers a dynamic picture of how a signal's frequency content changes over time. For the purpose of capturing unique variations in RF signals, spectrogram analysis is useful. It helps to detect transitory features, modulation patterns, and changes in signal properties across time.

2.3.2 Time-Domain Analysis

In radio frequency (RF) fingerprinting, time-domain analysis is a important signal processing technique that is used to study properties in the temporal dimension. In order to understand the temporal characteristics of radio frequency signals, this subsection dives into the essential aspects of time-domain analysis.

2.3.2.1 Pulse Analysis

The study of signal temporal characteristics, such as their intervals, duration's, and forms, is known as pulse analysis. It focus on the RF signals' time-dependent properties. Finding unique pulse characteristics helps to distinguish devices according to their time-domain attributes. For devices that use pulse modulation method, pulse analysis is really essential.

2.3.2.2 Modulation Analysis

Modulation analysis in the time domain studies how particular signal properties, such as amplitude, frequency, or phase, alter with time. Examining modulation characteristic improves the distinguishable powers of RF fingerprinting. It enables the recognizing of device-particular modulation patterns, which adds to the incomparable of RF signatures.

2.3.2.3 Timing Analysis

Timing analysis inquire the timing components of signal propagation. This includes studying packet timing, synchronization patterns, and other time-relevant aspects of RF propagation. Precise timing data helps in to distinguish device's RF signature. Timing analysis is essential for differentiating unique devices, especially in cases where synchronization patterns or certain temporal periods are indication of a device.

2.4 Summary

In short, Radio Frequency (RF) fingerprinting is a advanced method for identifying devices by examining their unique RF properties. These properties, include modulation, amplitude, phase, and frequency, which serve as cause for establishing fingerprints that are unique for each individual device. A fundamental understanding of RF fingerprinting involves studying the fundamentals of RF transmission, spectrum analysis, time-domain analysis, and advanced signal processing methods. By using both spectrum and time-domain analysis, RF fingerprinting provides a detail understanding of device signatures, which helps in accurate identification and discrimination of devices.

Chapter 3

Literature Review

The RF fingerprinting problem has been studied extensively in the past, with a large portion of that research concentrating on methods that call for domain-specific expert knowledge to meticulously create hand-crafted feature vectors on which to categorise the transmitters using common machine learning techniques. For feature extraction and classification, other authors have employed neural networks. Some of these models use a hybrid strategy that combines manually created feature vectors and neural network classifiers. We have divided our literature into two sections.

The objective of literature review is to perceive how features with machine learning and deep learning models has evolved over the time and how these architectures have been employed in specific emitter identification task.The chapter is divided into 2 sections: 3.1 reviews the feature based approach, 3.2 reviews the deep learning approach, 3.3 and 3.4 defines the research gaps and concludes the chapter.

3.1 Feature Based Approach

Radio frequency feature based specific emitter identification methods are typically based on artificial created radio frequency features and machine learning classifiers, there are several radio frequency artificial created features for SEI system, which can be broadly classified as instantaneous features, modulation features, and domain tranform features, as described below.

[12] examined the VMD's performance limits during RFF implementation. In order to achieve this, a thorough analysis of the effects of HOS features (variance, skewness, frequency, and phase) obtained from band-limited modes on the classification accuracy is performed. While making this, bluetooth devices are identified at various SNR ranges using the LSVM classifier. Figure 3.1 shows a figure that shows the general overview of the process.

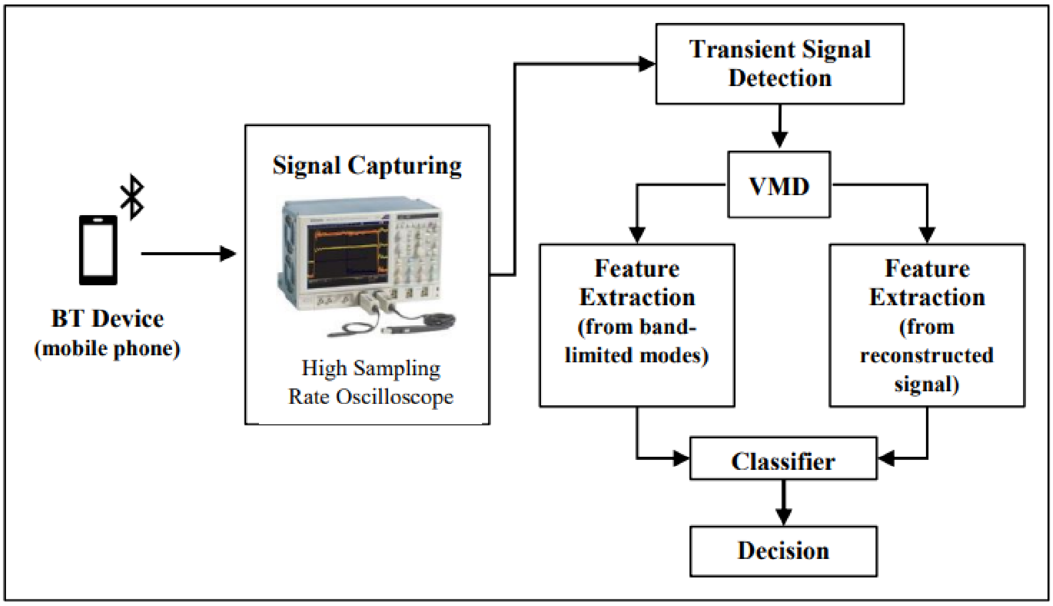

Figure 3.1: Operational diagram of the RFF implementation
[12]

[13] presented algorithms for extracting RF fingerprints from IoT devices based on statistical features. 10 IoT devices are successfully identified by extracting the instantaneous features of time domain signals, the properties of wavelet coefficients and time frequency spectrum. The identification accuracy of the feature extraction from time domain and time frequency spectrum can reach above 95% in 10 dB, and in a 15 dB environment, it is close to 100%. [14] examined the signal using non linear analysis across various do-

mains, because the generation process for the nonlinear RF fingerprints is complex. First, the CEEMDAN algorithm is used to reduce the impact of noise on the original signal. Then, the IMF of high-frequency components multidomain joint entropy features are extracted. Finally, the SVM classifier achieves a high recognition rate. The workflow of this technique is shown in Figure 3.2.

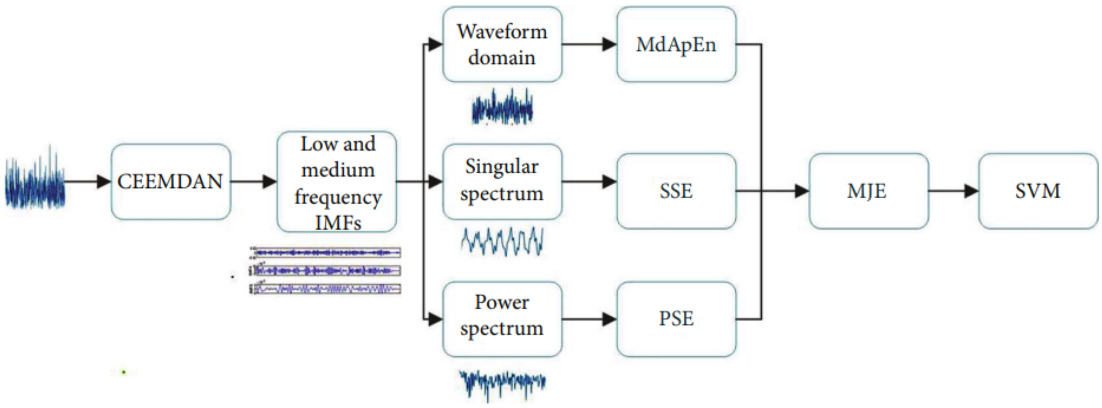

Figure 3.2: Flowchart of the CEEMDAN-MJE method
[14]

3.2 Deep Learning Approach

Deep learning models can be used to identify a specific emitter by examining the signal's or emissions' properties like frequency, amplitude, and phase. A deep learning model can be trained to identify the signature of various emitters using these characteristics. By comparing the characteristics of new signals to those of known emitters, the model can be used to determine the source of new signals after it has been trained.

Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short term memory (LSTM) networks are among the deep-learning architectures that may be utilised for particular emitter identification. The architecture used will be determined by the unique needs of the emitter identification job, such as the kind of signal being examined and the size of the dataset. The deep learning based SEI approaches may be divided into two types namely time domain signal and spectrogram.

3.2.1 Time Domain Based SEI Methods

Time domain signals are raw IQ signals or the break down of signal using empirical mode decomposition (EMD) and variational mode decomposition (VMD). [15] demonstrated that the use of a convolutional neural network can successfully differentiate between transmitters, even for devices that have the same make and type. To achieve this, the authors preprocessed the raw IQ signal samples of seven Zigbee devices and used them as input to the CNN. The network was trained to learn the unique RF characteristics of each device, such as the transmission power, modulation scheme, and channel impulse response. A LSTM and raw IQ samples based specific emitter identification technique was proposed by [16], but they concentrated on the issue that the identification performance of SEI degrades over time, so they introduced transfer learning to address this issue. A specific emitter identification technique based on LSTM was also proposed by [17], but their approach used training or test samples that were signal components that had been decomposed by empirical mode decomposition (EMD), intrinsic time-scale decomposition (ITD). More significantly, they looked into how multiple receivers could improve identification performance The LSTM-based cooperative identifier is shown in Figure 3.3.

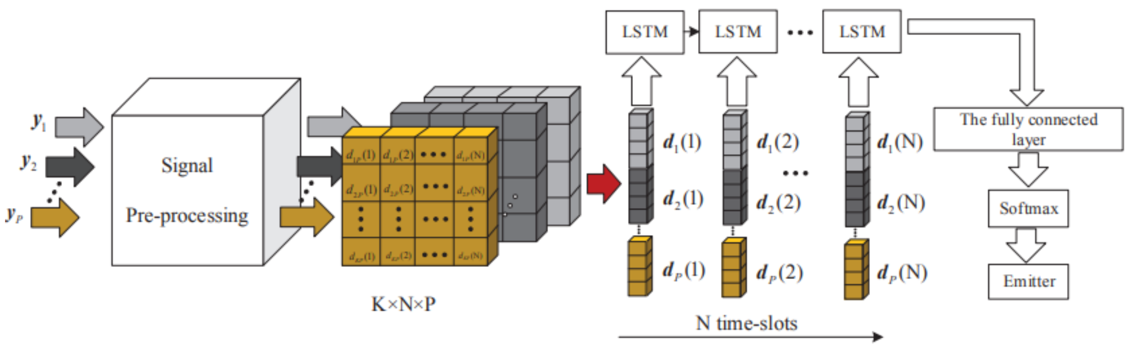

Figure 3.3: The block diagram of the LSTM-based cooperative approach [17]

3.2.2 Spectrogram Based SEI Methods

Bispectrum analysis and the fourier transform are frequently used in the spectrogram based specific emitter identification techniques.

[18] propoed an SEI method that utilizes the compressed bispectrum of the received signals through the use of CNNs. Normally, the high dimensional nature of the original RFF, such as the bispectrum, can lead to issues such as the ”dimension curse” and misidentification. However, by using the compressed RFF, it was able to reduce the impact of redundant information on identification. The CNN is able to learn and extract important features from the data, leading to an improvement in identification performance. In contrast to IQ based methods and fast fourier transform based techniques, the short time fourier transform based spectrogram and CNN based SEI technique was proposed by [19] which have shown superior identification performance. Additionally, the impact of carrier frequency offset (CFO) on the performance of identification is also disclosed. The estimated CFO is then incorporated to change the identification result and prevent performance deterioration. The architecture of spectrogram based CNN architecture is depicted in Figure 3.4.

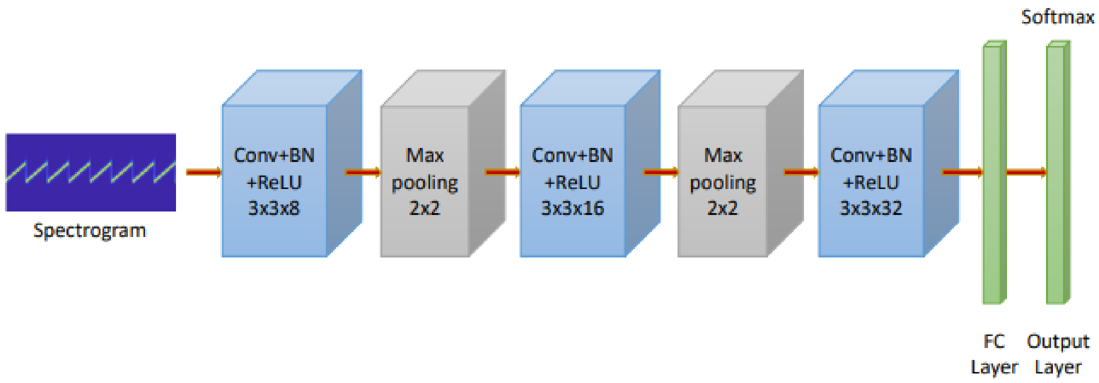

Figure 3.4: CNN architectures of spectrogram model
[19]

[20] presents a new method for analyzing signal features using a combination of short time fourier transform (STFT) and k means algorithm to achieve better recognition probabilities in low SNRs. The proposed method calculates time frequency spectrograms of

emitter signals, which are then analyzed using convolutional neural network (CNN) for automatic identification. Figure 3.5 presents the CNN model.

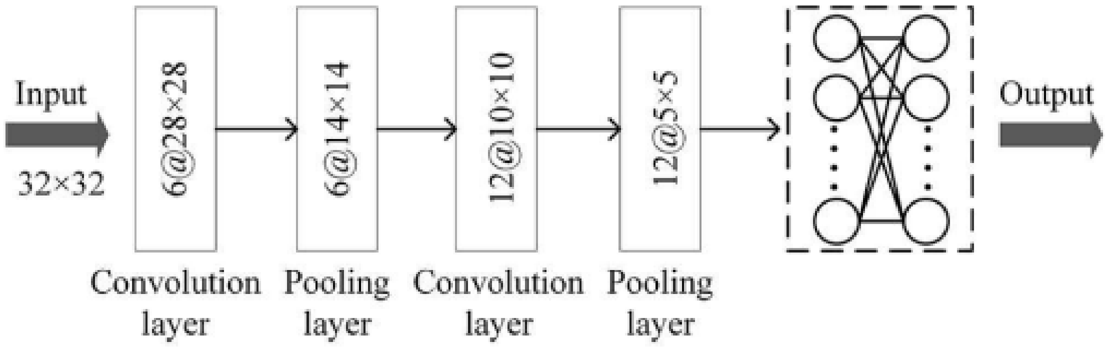

Figure 3.5: CNN Model
[20]

[21] applied one dimensional convolutional neural network for target recognition of radar. In this method ADS-B signal was used as a data sample and the original data was preprocessed using the FFT algorithm before being fed into a single dimensional convolution neural network for feature extraction. Additionally, when compared to the original time domain sampling signal, the FFT-based preprocessing method significantly increase the model's recognition accuracy. [22] proposed a SEI technique based on EMD feature extraction and deep neural network. The created CNN model shown in Figure 3.6 takes grey scale hilbert spectrum as an input and is efficient inlearning nonlinear features.

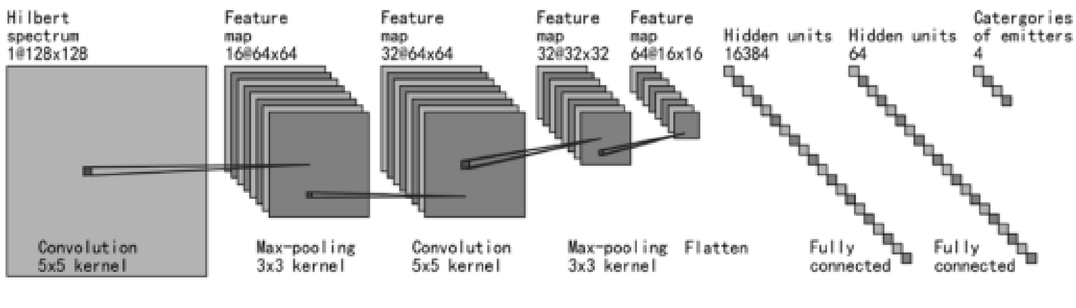

Figure 3.6: CNN Architecture
[22]

3.3 Research Gaps

In the Literature review for specific emitter identification, the following research gaps have been identified.

1. To identify the emitter in the presence of noise and interference.
2. Need scalable SEI technique that can handle large numbers of emitters without requiring extensive training data.
3. Need for SEI technique that can perform well in low SNR environments.

3.4 Summary

The literature survey revealed the current limitations of specific emitter identification. Over many years, SEI algorithms and methods have been created and improved. These include more conventional methods of signal processing as well as statistical and machine learning based approaches. Analyzing the spectral, temporal, modulation, and encoding aspects of RF signals is one of the SEI techniques. Deep learning methods like convolutional neural networks and recurrent neural networks have been the subject of recent research aimed at enhancing SEI performance. These techniques have demonstrated encouraging results in locating emitters in practical situations, and they could be a considerable advancement over conventional SEI techniques.

Chapter 4

Proposed Specific Emitter Identification

Specific emitter identification is an important task for improving the security of various wireless communication systems and to get better emitter recongnition accuracy under low signal to noise ratio (SNR). In this research, we have proposed a specific emitter identification technique based on discrete fourier transform and convolutional neural network. Figure 4.1 shows an overview of our proposed methodology. It starts with a filter which is used for denoising. The denoising process acts as a crucial preprocessing step to impove pattern visibility. It is intended to enhance performance by bringing down network complexity while successfully extracting complicated patterns. Denoising techniques enable the network to capture and distinguish tiny patterns even in environments with noise. After that discrete fourier transform is applied to extract frequency domain and phase information. The processed time domain, frequency domain and phase information of signal are fed to three parallel stacked CNNs which then extract features in parallel. Then the extracted features from each individual CNNs are concatenated and combined to pass on to the softmax layer for classification of emitters.

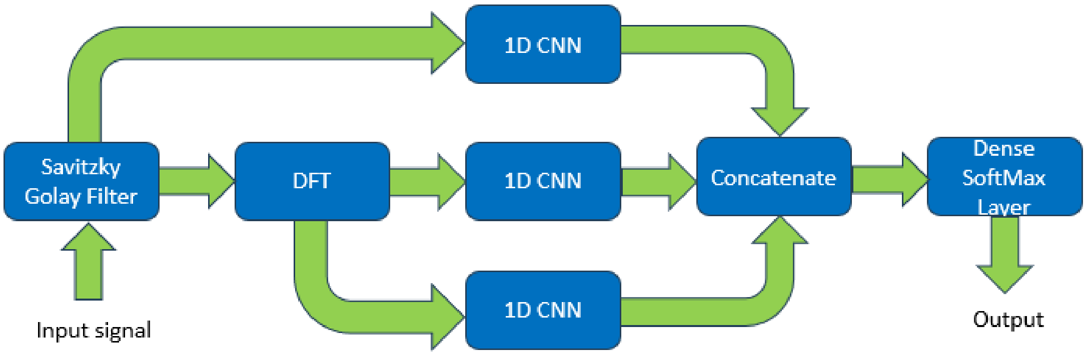

Figure 4.1: Illustration of proposed method.

4.1 Savitzky Golay filter

An technique for digital signal processing known as the savitzky golay filter is used to smooth data or identify a signal's derivatives. Abraham Savitzky and Marcel Golay introduced it in 1964. The filter operates by fitting a polynomial of a particular degree to a window of nearby data points and then calculating the smoothed value of the centre point in the window using the coefficients of that polynomial. The window size and polynomial degree are user-specified parameters that affect the trade-off between smoothing and maintaining signal features. A least-squares fitting procedure is used to calculate the coefficients a, which minimises the squared error between the original data points and the fitted polynomial.

$$e(n) = \sum_{n=-M}^{M} (p(n) - x(n))^2 \tag{4.1}$$

consider a group of data samples where n = 0,1,..M and M is the half width of the approximation interval. By selecting the window size and polynomial order, the new smoothed value is given by

$$Y_n = \sum_{i=(1-m)/2}^{(m-1)/2} C_i y_{n+i} \tag{4.2}$$

Here, C_i are the coefficients of the polynomial of degree N and y_i is the observed value. Compute the coefficients C_i for the polynomial using the least-squares method. C_i can be mathematically calculated as

$$C_i = (A^T A)^{-1} A^T y \tag{4.3}$$

where, A is a matrix containing powers of 2M+1 Values within the window and y is the observed value.

Figure 4.2 shows some signals before and after denoising.

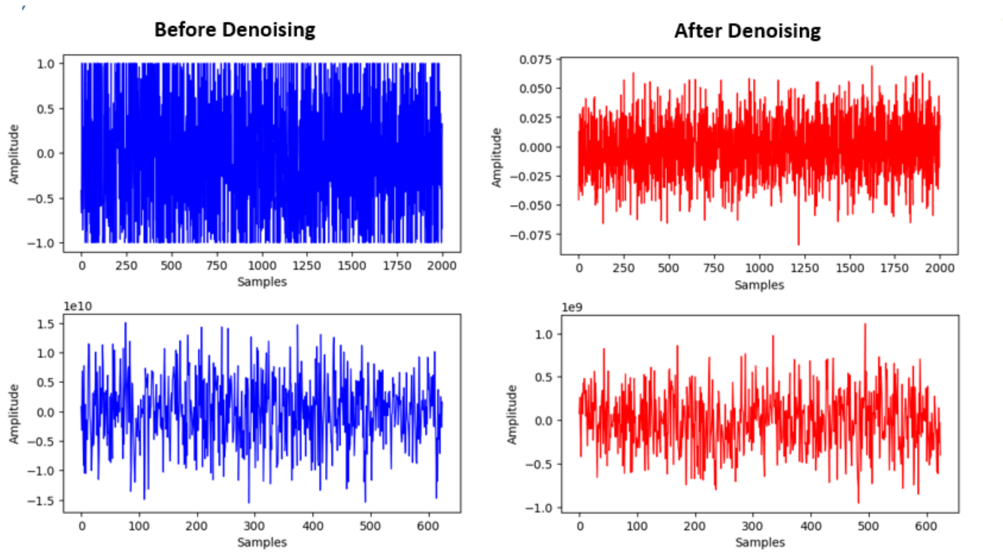

Figure 4.2: Denoising of Signals

4.2 Discrete Fourier Transform

The time domain signals which indicates its amplitude over the time instant or the sample number. However, in some circumstances, signal frequency content is more helpful than the signal samples.

The discrete fourier transform, or the DFT, is the technique used to convert time domain signal samples to frequency domain representation. The DFT also forms a connection between both representation the time domain and frequency domain. As a result, we can use the DFT to conduct frequency analysis on a time domain signal. A mathematical operation known as the DFT which transform a set of N complex numbers into an other set of N complex numbers, where each number in the output sequence denotes the amplitude and phase of a certain frequency component in the input signal.

$$X_k = \sum_{n=0}^{N-1} x[n] e^{\frac{-j2\pi kn}{N}} \tag{4.4}$$

The amplitude and the phase that buid the signal can be calculated from the complex array X_k are as follows (Im and Re denotes the Imaginary and Real parts of a complex number)

$$Amplitude = \frac{\sqrt{\mathrm{Im}^2(X_k) + \mathrm{Re}^2(X_k)}}{N} \tag{4.5}$$

$$Phase = tan^{-1}(\frac{\mathrm{Im}(X_k)}{\mathrm{Re}(X_k)}) \tag{4.6}$$

Figure 4.3 shows magnitude and phase plots of the dataset we used.

Furthermore, the DFT is frequently employed in a variety of different fields such as spectrum analysis, acoustics, audio, instrumentation, and communications systems.

4.3 Convolutional Neural Network

A Convolutional Neural Network (CNN) is represented as subset of machine learning, belonging to the broader family of artificial neural networks. These networks are utilized for various applications across different data types. CNNs are a specific network architecture tailored for deep learning algorithms, primarily applied in image recognition and tasks that involve pixel data processing. Convolutional Neural Networks are predominantly employed for classification and computer vision tasks, basic network stucture shown in

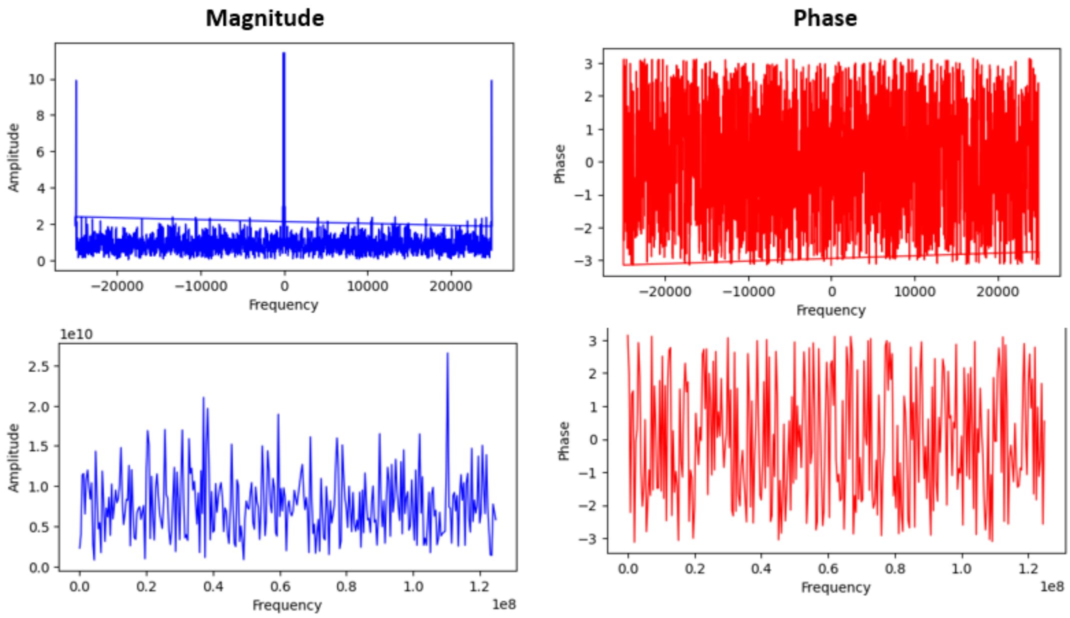

Figure 4.3: Magnitude and Phase Plot

Figure 4.4. Before the advent of CNNs, the process of identifying objects in images relied on intensive manual feature extraction methods. Nonetheless, CNNs have introduced a more efficient and scalable approach to tasks like image classification and object recognition. They achieve this by harnessing principles from linear algebra, notably matrix multiplication, to detect and recognize patterns within an image.

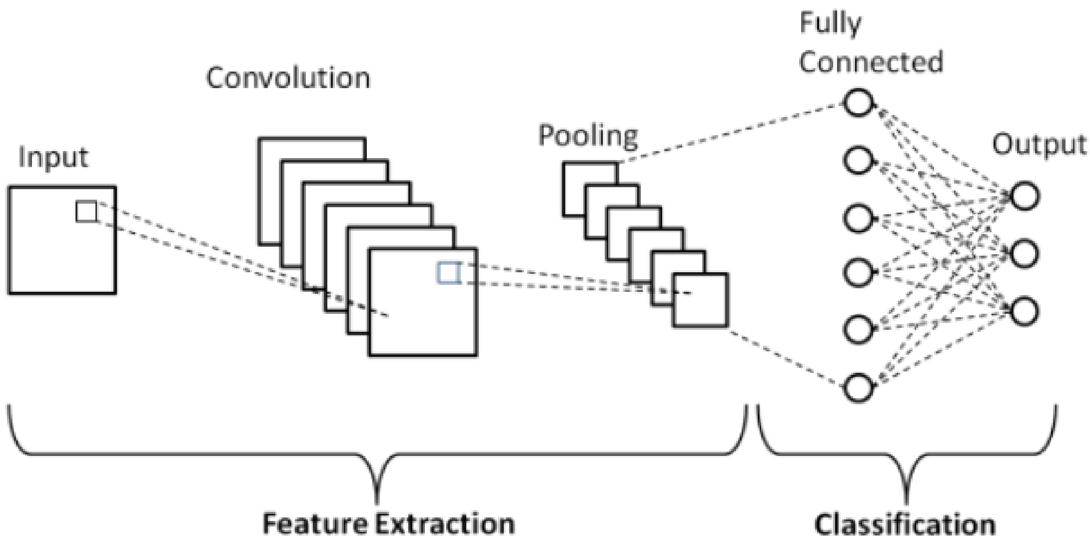

Figure 4.4: Basic CNN Stucture

4.3.1 Convolutional Layer

The bulk of computations within a Convolutional Neural Network (CNN) occur within the convolutional layer, which serves as the basic block of the neural network. In many cases, a second convolutional layer follows the initial one. The essence of the convolution operation entails a kernel or filter within this layer traversing the receptive fields of the image, systematically examining whether specific features are present in the image. For the numerous iterations, the kernel travels over the entire image. Following each iteration, a dot product computation occurs between the input pixels and the filter. This process results in a final output, known as a feature map. This convolutional layer is responsible for transforming the image into mathematical values, enabling the CNN to illustrate the image and extract pertinent patterns from it. The convolution operation can be mathematically expressed as

$$Y(i,j) = \sum_{m}\sum_{n} X(i-m, j-n).K(m,n) \tag{4.7}$$

Where Y(i,j) is the value at position (i,j) in the output feature map. X is the input feature map. K is the kernal or filter. m and n are the indices of the elements in K.

4.3.2 Pooling Layer

Pooling layer plays a pivotal role in lowering the spatial dimensions of the convolved feature. Pooling operation sweeps a filter across the whole input, but the difference is that this filter does not contain any weights. Its primary purpose is to reduce the computational demands involved in processing data by diminishing the dimensions and also results in some information loss. There are two principal types of pooling employed in this layer average pooling and max pooling. Max-pooling is a popular pooling operation:

$$Y(i,j) = max_{p,q \in R_{i,j}} X(p,q) \tag{4.8}$$

Where $R_{i,j}$ is the local region in the input feature map corresponding to the output location (i,j).

4.3.3 Fully Connected Layer

The term fully-connected layer is quite straightforward. Unlike the limited connected layers, where the pixel values of the input image are not directly related to the output layer. In the fully-connected layer, every node in the output or last layer establishes a direct connection with a node in the previous layer. The main goal of this layer involves classification, relying on the features extracted from preceding layers and their diverse filters. All the layers in the CNN are not entirely connected because it would give unessential dense network. It would also increase the losses and affect the output quality, and it would be computationally expensive. The fully connected layer can be expressed as

$$Y = f(WX + b) \tag{4.9}$$

4.3.4 Activation Function

The activation function plays a crucial role in determining whether a neuron should be activated. It achieves this by computing the weighted sum and incorporating bias. The role of the activation function is to give output from a set of input values fed to a node (or a layer) and to inject non linearity into the neuron's output.

ReLu (Rectified Linear unit) preferred over other nonlinear activation functions due to its ability to rapidly convergence.ReLU speeds up deep neural network learning by introducing a simple thresholding method that allows positive values to pass through unchanged. ReLU is an appealing option because it improves model convergence by reducing the vanishing gradient problem and speeding up training-phase optimisation.

$$f(x) = \max(0, x) \tag{4.10}$$

4.3.5 Loss Function

A loss function is an important component in the field of machine learning. It serves as a statistical technique that determines the error between a machine learning or deep learning model's predicted outputs and the actual output labels. The main aim of this function is to increase the model performance by minimizing the loss, which will guide to a reduction in the model's errors obtained on the training data. The loss function is an important aspect in the machine learning or deep learning, since it not only allows you to assess the model's performance but also gives essential guidance during the optimization phase. The loss function engaged is determined on the type of model or the task being performed. For instance, mean squared error is regularly applied in regression based tasks and categorical cross-entropy loss is used in classification based activities.

$$L = -\frac{1}{N}\sum_{n=1}^{N}[y_t(n)\log_{10}(\hat{y}(n)) + (1 - y_t(n))\log_{10}(1 - \hat{y}(n))] \tag{4.11}$$

where, $y_t(n)$ shows the true output label, $\hat{y}(n)$ is the predicted output generated from model.

4.3.6 Backpropagation

Backpropagation in a Convolutional Neural Network (CNN) is an essential training procedure that allows the network to learn from its errors during training procedure and improve the parameters, such as weights and biases, to have better performance on specific tasks like image classification etc. For training feed forward neural networks backpropagation is a popular approach used nowadays. It computes the gradient of the loss function relative to the network weights. It is far more efficient than simply computing the gradient for each weight. This efficiency enables gradient methods to be used to train multi layered networks and update weights to minimize loss.

$$\theta = \theta - \alpha \nabla L(\theta) \tag{4.12}$$

Where θ represents network parameters (weights and biases), α is the learning rate and $\nabla L(\theta)$ is the gradient of the loss function with respect to θ.

4.4 Summary

In the proposed methodology it integrates denoising, discrete Fourier transform, and parallel CNNs to enhance specific emitter identification accuracy in wireless communication systems, particularly in challenging low SNR conditions. The combination of these techniques aims to improve the model's ability to discern subtle patterns and features, ultimately contributing to the overall security and reliability of wireless communication systems.

Chapter 5

Experiments and Results

The proposed model has been tested on walkie talkie dataset and open source cellphone dataset. An ablation study has been carried out on how our proposed model performed with various SNRs and compared with the existing methods in terms of accuracy. This chapter is divided into 5 sections: Section 5.1 explores the dataset, Section 5.2 contains implementation details, 5.3 describes the evaluation metrics, Section 5.4 contains detailed analysis of results from ablation studies and Section 5.5 concludes the chapter.

5.1 Dataset

This section covers the information about two different datasets used for the evaluation of the proposed method. One dataset is based on VHF radios that was generated in a real-world environment, other dataset consist of bluetooth signals of cellphone. The datasets are splited into 80 percent training data and 20 percent testing data.

5.1.1 Walkies Talkies Dataset

Eleven walkie talkies were used in our trials, which were done as part of the extensive field testing phase, and their frequencies were adjusted to fall between 136 and 176 MHz.

The signals were captured at a particular frequency of 136 MHz, with a channel bandwidth of 25 kHz, and in a multi-path environment. A total of 100 signals, each lasting 2 to 5 seconds, were recorded for each walkie-talkie, and this data was gathered at a sampling rate of 50 kS/sec on each individual emitter. To evaluate the performance of our technique at various SNRs, we used synthetic Additive White Gaussian noise (AWGN) during simulation. This enabled us to systematically assess the algorithm's robustness and efficacy in tough noise settings. Overall, we captured and processed 20900 signals, each with 2000 samples, which were strategically used for training and validation of the proposed technique. 5.1 shows the some walkie talkie signals

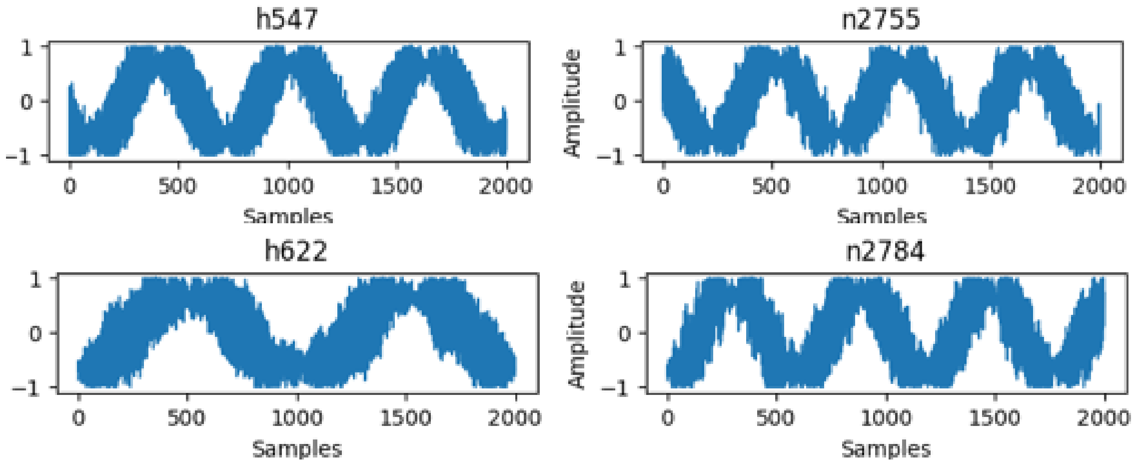

Figure 5.1: Walkie Talkie Signal.

5.1.2 Cellphone Dataset

Bluetooth signals was captured at an isolated laboratory at Atilim University, Ankara, Turkey from different smartphone brands with a sampling rate of 250Ms/sec. A set of 16 smartphones of various models produced by five manufacturers were used in the data collection. In the dataset, there are 4950 records of Bluetooth signals. For one smartphone, there are 300 records and for each record it consists of 625 samples. To evaluate the performance of our technique at various SNRs, we used synthetic Additive White Gaussian noise (AWGN) during simulation. This enabled us to systematically assess the algorithm's robustness and efficacy in tough noise settings. 5.2 shows the some cellphone signals

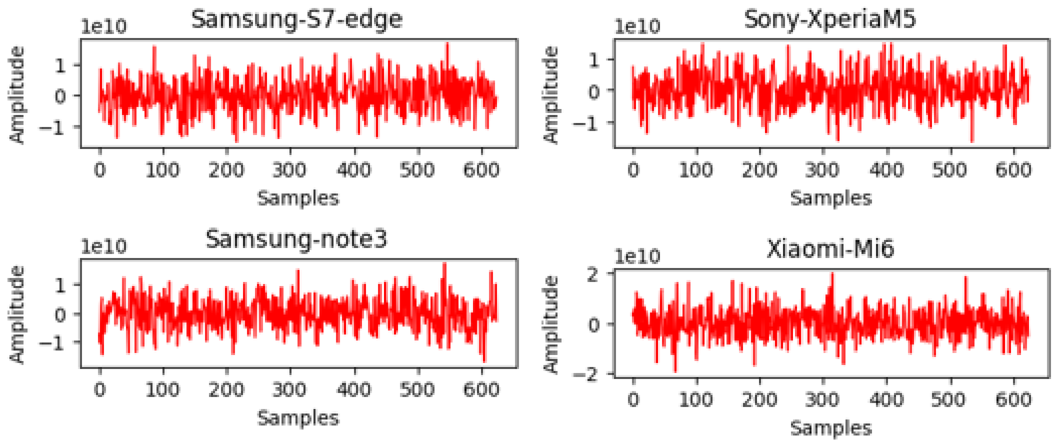

Figure 5.2: Cellphone Signal.

The summary of the two dataset used to evaluate the performence of our technique are as follows.

Table 5.1: Dataset Summary

Description	Walkies Talkies	Cell Phones
Sampling Frequency	50 Ks/Sec	250 Ms/Sec
Classes	11	16
Records	20900	4950
Samples	2000	625
Signals per Class	1900	300

5.2 Implementation details

Convolutional Neural Networks (CNNs) have proven to be highly effective in discerning complex patterns in signals. They excel at extracting features through a sequence of mathematical operations, harnessing the strength of convolutional and pooling layers to filter out noise, showcasing their impressive capabilities in this regard. 5.3 and 5.4 shows the proposed stacked architecture, convolutional layer with 64 filters of kernal size 3 and dense softmax layer.

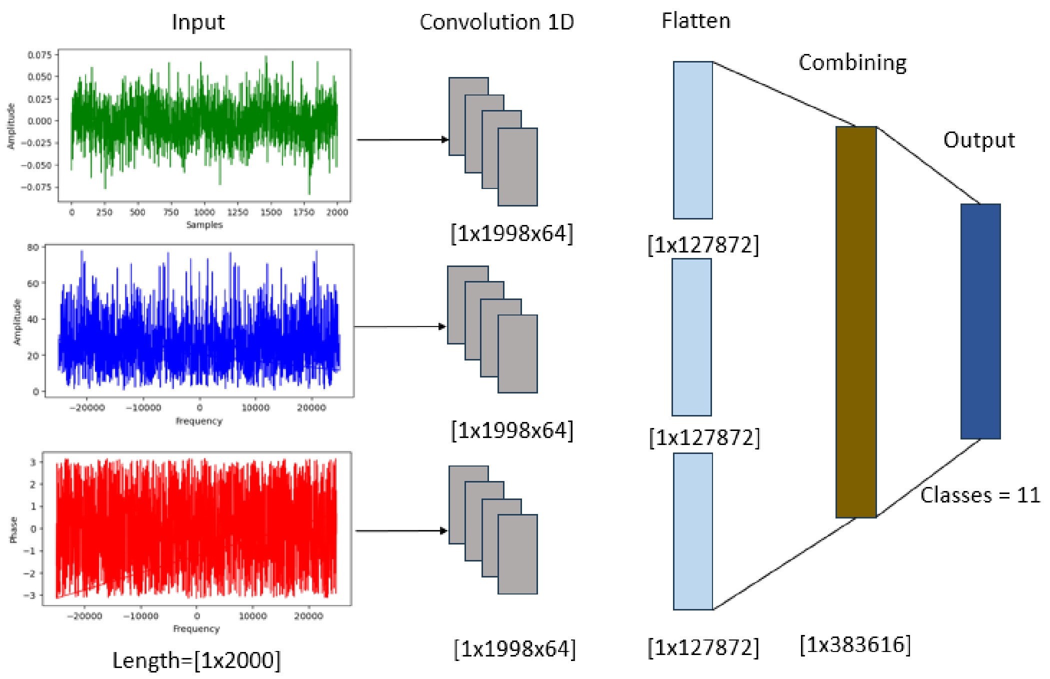

Figure 5.3: CNN Network Architecture

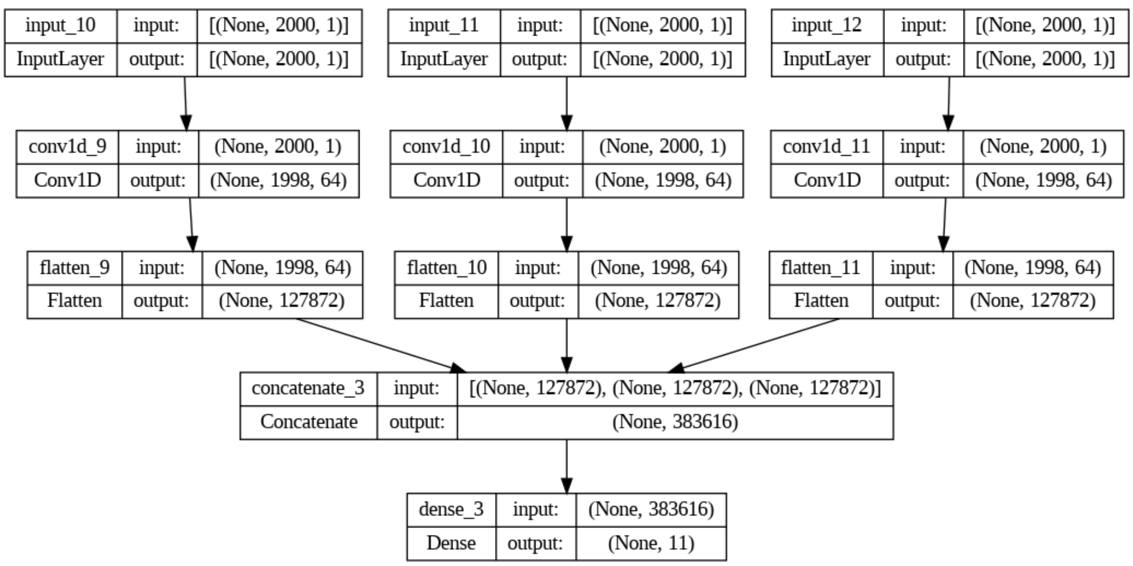

Figure 5.4: CNN Layer wise Configuration

This design smoothly incorporates denoising directly within the network, strengthening the CNN's ability to handle demanding situations with high levels of noise. The denoising step serves as a pivotal initial phase, enabling subsequent layers to concentrate on extracting pertinent features that are resistant to noise interference. Consequently, this suggested architecture presents a hopeful remedy for enhancing the unclear outlines in the signal caused by noise, facilitating the network in effortlessly discerning distinctive patterns.

The proposed model is implemented using keras and trained on a T4 GPU. The AdamW optimizer is used to fine-tune the network for 100 epochs with a batch size of 64.

5.3 Evaluation Metrics

We assessed the performance of our approach in RF Fingerprinting by employing metrics such as classification accuracy, confusion matrix, and benchmarking against various established deep learning methods. This evaluation, conducted across different Signal-to-Noise Ratios (SNRs), aims to gauge the efficacy of our proposed method in comparison to existing techniques.

5.4 Quantitative Results

To evaluate the proposed classification model, we have conducted detailed experiments. All of our experiments are carried on walkies talkies and cellphone dataset. We conducted a comprehensive analysis to understand how the accuracy of the proposed model is affected by varying the SNRs(Signal to noise ratio). The results yielded intriguing observations regarding the model's performance are shown in Table 5.2 and 5.3 for both datasets.

Table 5.2: Classification Accuracy of Walkies Takies Dataset

SNR	**Walkies Talkies Accuracy**
0 dB	90 %
5 dB	95 %
10 dB	96.3 %
15 dB	97.6 %
20 dB	98.4 %

Table 5.3: Classification Accuracy of Cellphone Dataset

SNR	Cellphone Accuracy
0 dB	92 %
3 dB	95.5 %
6 dB	96.3 %
9 dB	98 %
12 dB	98.4 %
15 dB	99.2 %

It can bee seen from Table 5.2 and 5.3, Thorough evaluation across 100 iterations, we observed highly encouraging outcomes. Specifically, when the Signal-to-Noise Ratio (SNR) exceeds 5 dB, our proposed method demonstrates an outstanding average accuracy exceeding 97%. This indicates its proficiency in accurately discerning walkie-talkie and cellphone signals, particularly in favorable SNR scenarios. The notable precision achieved in these tests underscores the significant potential of our approach for practical applications, especially in contexts where precise identification of walkie-talkie and cellphone signals holds paramount importance for communication security and administration.

Moreover the findings from confusion matrices shown in 5.5 and 5.6, further reinforce the model's accuracy, highlighting its proficiency in classifying signals accurately. The matrix's diagonal elements depict the count of accurate classifications for each class, providing a measure of the model's precision in specific categories. In contrast, the upper and lower triangular matrices reveal cases of misclassifications, offering a transparent view of the method's errors.

5.4.1 Comparison with Literature

After finalizing the model En-ConvNet, we also performed comparative analysis on walkies talkies dataset and cellphone dataset with following existing state of the art techniques.

- Inphase and Quadrature Convolutional Neural Network, IQ-CNN

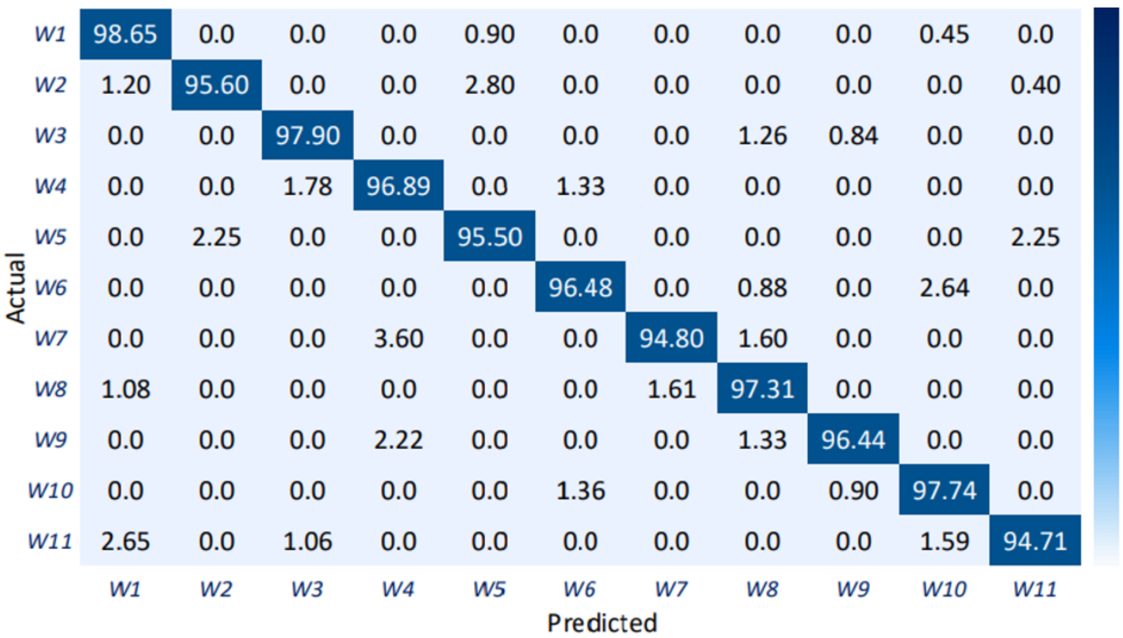

Figure 5.5: Walkies Talkies Confusion Matrix

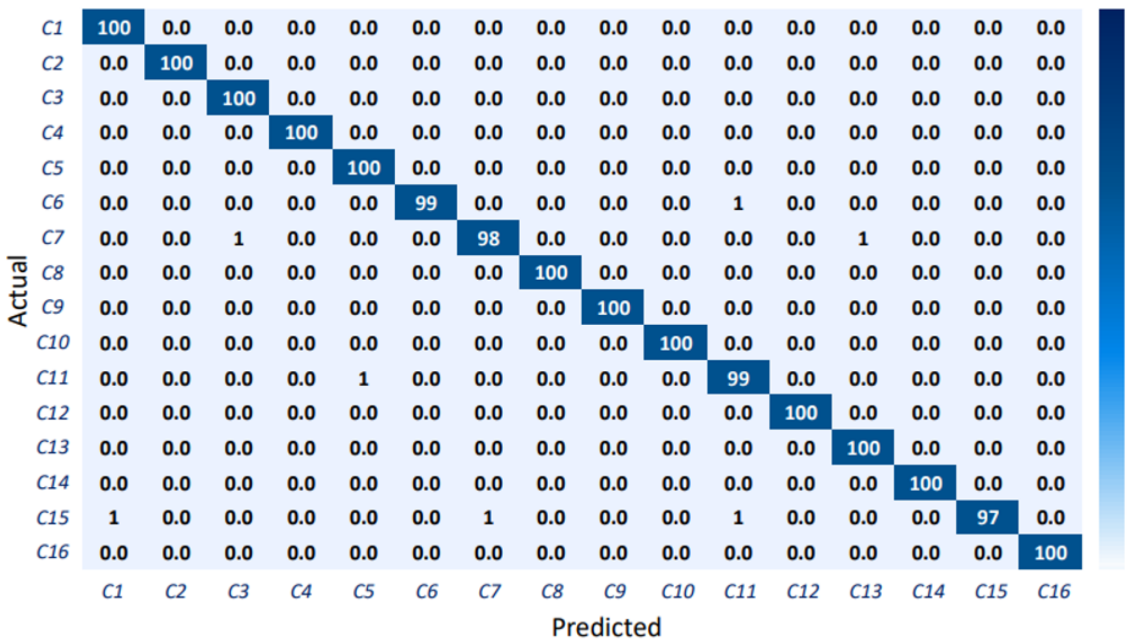

Figure 5.6: Cellphone Confusion Matrix

- Short Time Fourier Transform Convolutional Neural Network, STFT-CNN
- Discrete Wavelet Transform Convolutional Neural Network, DWT-CNN
- Empirical Mode Decomposition Convolutional Neural Network, EMD-CNN

Figure 5.7 ,5.8, 5.9 and 5.10 illustrates our discoveries, showcasing that the En-ConvNet approach outperforms other established deep learning methods. Specifically, as the Signal-to-Noise Ratio (SNR) falls below 15 dB, the classification accuracy of the existing methods noticeably declines. This suggests that these methods face challenges in handling substantial noise levels, which in turn hinders their capability to extract pertinent features from the RF fingerprints effectively.

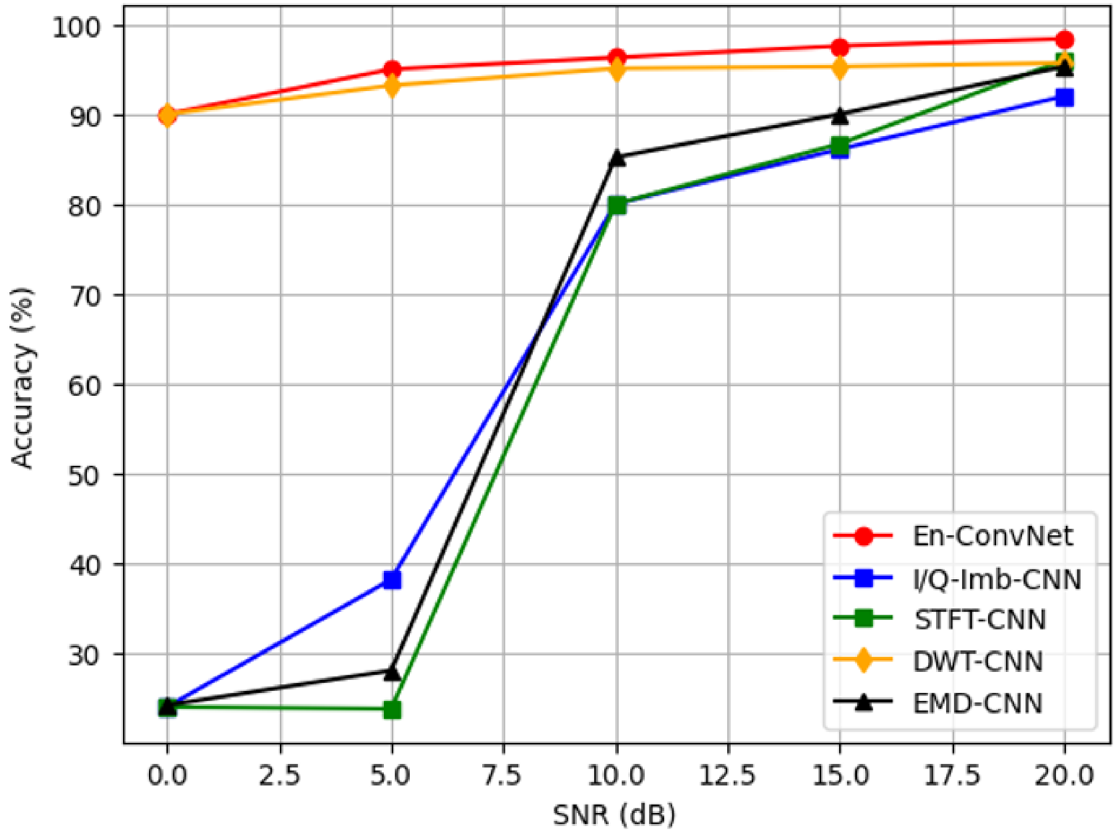

Figure 5.7: Comparision of Walkies Talkies Dataset with Existing Methods

SNR	En–Conv Net	I/Q- Imb - CNN	STFT-CNN	DWT-CNN	EMD-CNN
0	90	24	24	90	24.2
5	95	38.2	23.8	93.2	28.06
10	96.3	80	80	95.1	85.2
15	97.6	86.1	86.7	95.3	90
20	98.4	92	96	95.7	95.3

Figure 5.8: Accuracies of Walkies Talkies Dataset with Existing Methods

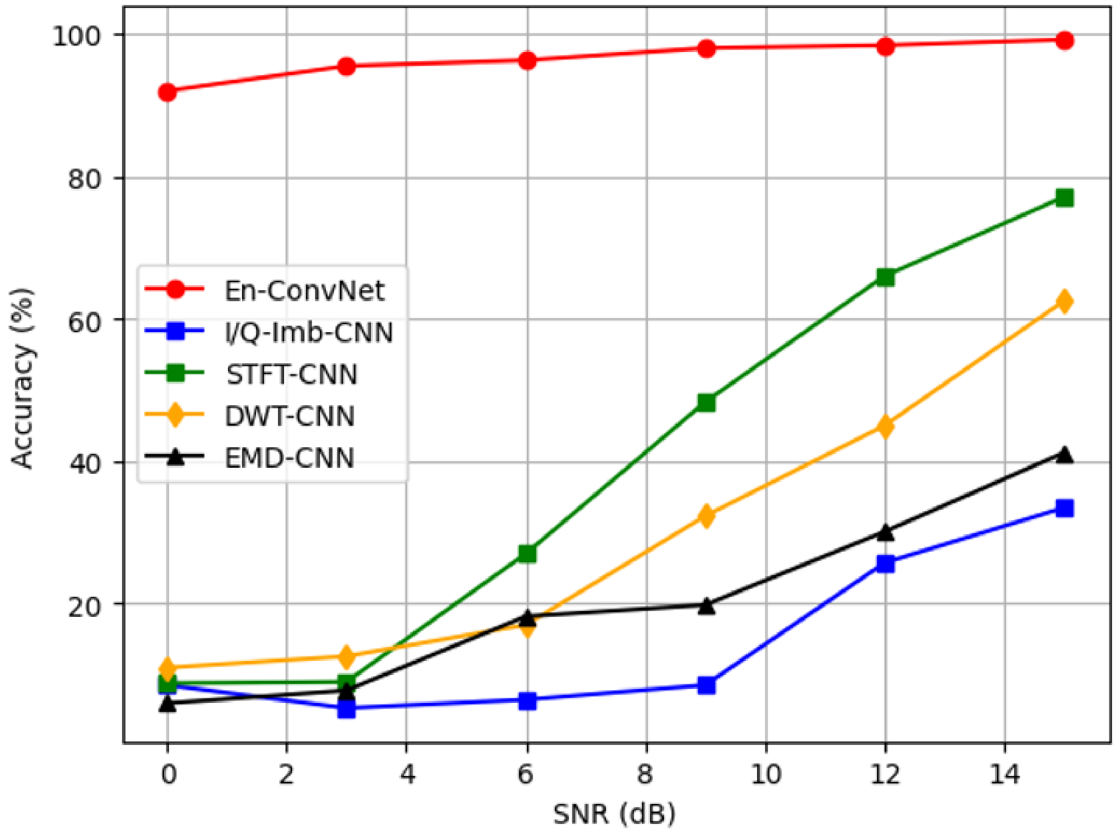

Figure 5.9: Comparision of Cellphone Dataset with Existing Methods

SNR	En-Conv Net	I/Q- Imb - CNN	STFT-CNN	DWT-CNN	EMD-CNN
0 dB	92	8.55	8.8	11	6
3 dB	95.5	5.32	9	12.6	7.8
6 dB	96.3	6.5	27	17	18.2
9 dB	98	8.55	48.3	32.3	19.8
12 dB	98.4	25.72	66	45	30.1
15 dB	99.2	33.47	77.1	62.5	41.2

Figure 5.10: Accuracies of Cellphone Dataset with Existing Methods

Nonetheless, the En-ConvNet approach distinguishes itself by maintaining its robustness even when confronted with elevated levels of noise and low Signal-to-Noise Ratios (SNRs). This durability can be attributed to the integration of the Savitzky-Golay Filter (SGF) within the proposed deep learning framework. The SGF plays a pivotal role in enhancing the delineation of the RF fingerprints, allowing the En-ConvNet to extract discernible and meaningful patterns with notable precision.

5.5 Summary

This chapter has analyzed the datasets, implementation details and results of proposed architecture quantitatively on various Signal-to-Noise Ratios (SNR). A detailed comparison with different methods has been elaborated in Section 5.4. Chapter 6 will discuss the shortcomings and future work related to our research.

Chapter 6

Conculsion and Future Work

6.1 Discussion

In today's world, there is an increasing demand for advanced computational systems. Deep learning techniques have becoming increasingly prominent. Their outstanding capacity to recognize patterns has led to significant application across numerous disciplines. CNNs excel in categorization tasks, making them a standout deep learning method. This is mainly due to their ability to automatically extract features. CNNs are designed to detect and learn relevant patterns and properties from input data, making them extremely effective in tasks like image and signal categorization. This unique capability in automatic feature extraction allows CNN-based techniques to thrive in a variety of applications, including Signal Emitter Identification (SEI). CNN-based approaches perform very well in SEI, where precise recognition and classification of complicated and unique signal features is critical.

The study evaluates the performance of the En-ConvNet technique on two different datasets, specifically walkie-talkies and cell phones. The purpose is to investigate how variations in signal-to-noise ratio (SNR) affect classification accuracy. On both datasets, En-ConvNet showed outstanding performance, when compared to other deep learning techniques, showing exceptional robustness in low SNR state. The results generated from the confusion matrices further highlights the model's precision, showing its ability to appropriately classify the signals.

6.2 Conclusion

This research study provide a unique ensemble neural network that greatly highlights the importance of feature extraction and classification of devices. This is obtained by applying stacked multivariate lightweight Convolutional Neural Networks (CNNs) to signals from diverse domains and intregating savitzky golay filtering as a denoising step. In particular, when applied on real-world walkie-talkie dataset under low Signal-to-Noise Ratio (SNR) conditions, our proposed model also outperforms more complex deep neural networks. Furthermore, the model also shows outstanding performance on a publicly available dataset which are of cell phone signals. In particular, when the SNR goes 5 dB and its beyond, the classification accuracy surpasses an amazing 95% on both datasets, showing strong proof of the ensemble neural network's efficiency in managing complex signal processing tasks.

6.3 Future work

Potential possible improvement for future research work in Specific Emitter Identification (SEI) highlights the following:

- **Advanced Signal Processing Techniques:** In order to improve the accuracy and flexibility of SEI systems, we can inquire into more complicated signal processing techniques.
- **Machine Learning and AI:** More evolution in artificial intelligence, deep learning, and machine learning methodologies can result in SEI techniques that can be more reliable and are more efficient.

- **Quantum Computing for SEI:** Investigate how quantum computing could potentially offer methods for SEI tasks, especially in scenarios when dealing with large-scale data.

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