MODULATION CLASSIFICATION FOR COGNITIVE RADIO NETWORKS USING DEEP LEARNING

report submitted to the SASTRA Deemed to be University as the requirement for the course

MCSCEC1001: PROJECT PHASE II

Submitted by

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JULY 2022

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BONAFIDE CERTIFICATE

This is to certify that the report titled "Modulation Classification for Cognitive Radio Networks using Deep Learning" submitted as a requirement for the course, **MCSCEC1001: PROJECT PHASE II** for M.Tech Communication systems programme, is a bonafide record of work done by **Mr. Kandula Sai Tinendra Kumar (Reg No: 122102007)** during the academic year 2021-2022, in the school of EEE.

Signature of the Guide:

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DECLARATION

I declare that the thesis titled "Modulation Classification for Cognitive Radio Networks using Deep Learning" submitted by me is an original work done by me under the guidance of **Prof. Dr. Ramya Vijay, School of Electrical and Electronics Engineering, SASTRA Deemed to be University** during the tenth semester of academic year 2021-2022, in the **School of Electrical and Electronics Engineering.** The work is original and whenever I have used material from other sources, I have given due credit and cited them in the text of the thesis. The thesis has not formed for the award of any degree, diploma, associate-ship, fellowship or any similar title to any candidate of any university.

Signature of candidate: Kandula Sai Tinendra Kumar

Name of the candidate: Kandula Sai Tinendra Kumar

Date: 08/07/2022

ACKNOWLEDGEMENT

First of all, I express my gratitude to Prof. **Dr. S.Vaidhyasubramaniam**, Vice Chancellor, **Sastra Deemed to be University**, who provided all facilities and necessary encouragement during the course of our study. I extend my sincere thanks to Prof. **Dr. R.Chandra Mouli** Registrar, Sastra Deemed to be University for providing the opportunity to pursue this course. It is my privilege to express my sincerest regards to **Dr. K. Thenmozhi** Dean (SEEE) and **Dr. K. Sridhar**, Associate dean (ECE) who motivated me during the course.

I express my sincere indebtedness towards my guide **Prof. Dr. Ramya Vijay, School of Electrical and Electronics Engineering**, Sastra Deemed to be University, Thanjavur for her invaluable guidance, suggestions and supervision throughout the work. Without her kind patronage and guidance the project would not have taken shape. I would also like to express my gratitude and sincere regards for her kind approval of the project, time to time counselling and advices.

I owe sincere thanks to all the faculty members in the department of Electronics and Communications Engineering for their kind guidance and encouragement from time to time.

ABSTRACT

Over the years, wireless technology has advanced at an incredible pace, becoming an inextricable part of our daily lives. Each communication generation strives to provide a larger coverage area, a higher number of users, a higher bit rate, and increased spectrum efficiency and power consumption. Communication systems must deal with a variety of limitations that obstruct the transmission of signals. To date, communication engineers have primarily employed statistical models to build wireless systems that simulate the consequences of channel damage. The complexity of creating new communication systems, on the other hand, is fast increasing as the number of wireless devices grows. As a result, many researchers are focusing on machine learning (ML) and deep learning (DL) techniques, especially as 6G research begins.

Radio modulation classification using a deep learning approach is the topic of this thesis. The thesis discusses two architectures that use convolutional and recurrent neural networks. The main goal is to reduce total number of parameters for each model by evaluating during the design phase, as it can have a significant impact on a deployed model's memory footprint. Keras, a Python interface for neural networks, was used to create the architecture. In this phase, to improve the accuracy in lower SNR values, architectures like CLDNN will be trained and evaluated on current and other datasets. The outcomes are compared to those of earlier research articles on the subject.

Specific Contribution:

- To design architecture with fewer parameters than conventional approaches while keeping good accuracy and reducing computational complexity.
- The DL classifier can accommodate a large range of modulation schemes while remaining relatively simple.

Limitations:

- Although data measured in a laboratory might be helpful to get a gist of the network’s performance, the need for a robust real-life dataset is very important to obtain an efficient and robust classifier.

TABLE OF CONTENTS

Abbrevations:

CNN – Convolutional Neural Networks

CLDNN – Convolutional Long-Short-Term-Memory Deep Neural Network

DL – Deep Learning

ML – Machine Learning

FB – feature based

GRU – Gated Recurrent Unit

SNR – Signal to Noise Ratio

CHAPTER 1

INTRODUCTION

Over the years, wireless technology has advanced at a breakneck pace, becoming an inextricable part in our lives. Each generation of communication strives in order to provide a larger area coverage, a larger no of users, a higher bitrate, and increased power consumption and spectrum efficiency. With fast-growing number of wireless devices, the difficulty of building new communication systems is continuously increasing [1]. As a result, many researchers are focusing on machine learning (ML) and deep learning (DL) techniques, especially as 6G research begins.

Machine learning and deep learning techniques can be applied to wireless networks to enhance dynamic spectrum access, energy efficiency, and radio resource allocation. For the information to be transmitted successfully, signal detection and modulation categorization are required. Automatic modulation classification (AMC) can be used by cognitive radio (CR), which was created to scan the spectrum around it to allow more variable DSA. It can dynamically change and modify factors like bitrate, frequency and power by scanning all the surroundings and improving the system's performance [16].

Nowadays, Automatic Modulation Classification (AMC) approaches use either a likelihood-based approach or a feature-based one. The likelihood-based approach can be very precise, but it also uses a lot of computing power. If there are many unknown parameters in the received signal, finding a good analytical solution can be difficult. In the feature-based method, classifiers must extract a variety of features from the input information. Computational complexity, quantity of modulation schemes, and accuracy are frequently traded off. In the last 5 years, there's been an emphasis in using DL to take a different approach to AMC. There are no additional features or signal specifications needed for the DL technique.

The goal of this thesis is to employ deep learning architecture to classify radio modulation. CNN and CLDNN are the proposed architectures that are trained and assessed using two datasets. The primary aim was to create designs that require fewer parameters while still keeping excellent accuracy. Other widely regarded papers [3,4] have up to fifty times as many parameters as the structures described in this thesis. To gain a better picture of their performance, they are tested on multiple datasets.

<u>**CHAPTER 2**</u>

OVERVIEW OF DIGITAL COMMUNICATION SYSTEM

Each communication system consists of three major components. They are transmitter, a receiver, and a channel. When an information source generates some signal along with message, it is converted by a transmitter into a format that is appropriate for the characteristics of the channel. The signal is subsequently transmitted to the receiver on a channel, which is positioned at a different location than that of transmitter. However, because of the received signal is distorted due to channel faults. Attenuation and fading effects are added to the broadcast signal, as well as a variety of noises. The recipient reassembles the signal so that a user can see a readable version of the real message.

Because modulation categorization is such an essential part of communication systems, this chapter is aimed to introduce them. Some blocks of communication system are briefly described in this chapter. More descriptions can be found in [5,6].

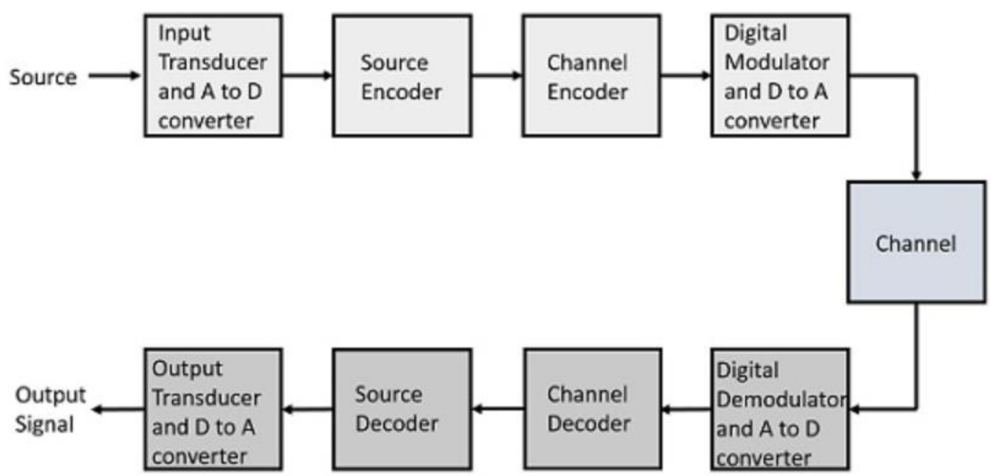

Fig 2.1: Block diagram of digital communication systems [8]

2.1: Source Transmitter:

The transmitter techniques that must be used for signal transmission are covered in this section. In the upper portion of Fig. 2.1, you can observe these stages.

2.1.1: Information Signal:

If some input source signal is considered to be analog then the signal is converted to digital using an analog-to-digital converter.

A signal carrying data is usually a low-pass signal that is, they are those that have their frequency components centred around the zero frequency in communication. The information signal cannot be directly sent through a wireless communication channel since it operates at higher frequencies. To match the channel parameters, a conversion to a higher-frequency band-pass is required. For the sake of simplicity, the abstract model using mathematical language described here assumes that the time-dependent features of the signal are always known in advance. Many signals in actuality, on the other hand, necessitate a probabilistic model since they contain numerous unknown variables.

The carrier frequency fc is close to the spectrum of a band-pass. It's very prevalent in radio transmission. The signal's bandwidth 2B is smaller than fc, Consequently, it is known as a narrow-band signal. A low-pass version of the actual signal can be used to express any communication bandpass signal. It is significantly easier to handle the band-pass signal when dealing with the low-pass version. Due to reduced necessary sampling rates, the low-pass version has fewer amounts of collected information.

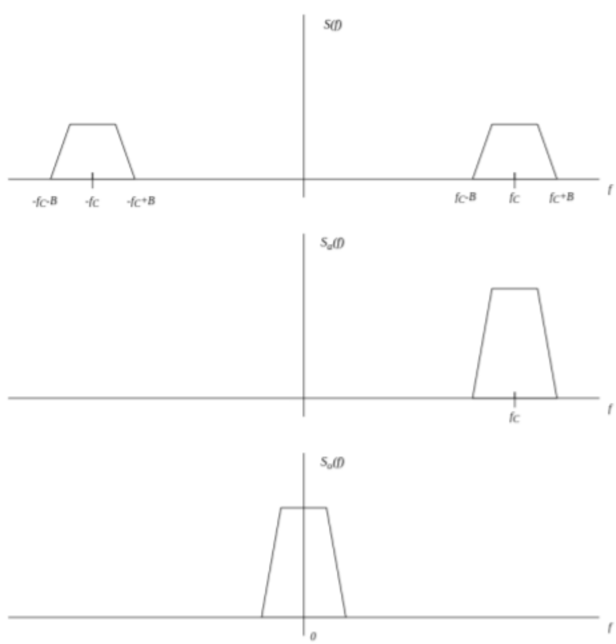

Fig 2.2: Bandpass signal to analytic [7]

2.1.2: Channel Encoder:

The channel encoder adds redundancy to the transmitted signal and modifies it to fit the transmission channel in contrast to source encoder. The channel encoder's additional redundancy aids in error correction at the receiver. Signal leakage, other sorts of interference, and other factors might create these errors during transmission.

2.1.3: Source Encoding:

Unnecessary bits from the input data stream are removed by source encoder. Compression, which can be classified as lossless or lossy, results in a reduction in the no of bits. For lossless compression, the number of bits is decreased in a way that enables future complete restoration of the source. This is not achievable with lossy compression, which has a limit on the amount of distortion that can be tolerated. In any case, the signal bandwidth and transmission channel baud rate are both reduced as a result of this block.

2.1.4: Components of Modulator:

The process of modulation modifies the characteristics of the carrier frequency in accordance to source signal**.** The information that is transmitted can either be digital or analog, and both use a sine signal with high frequency as carrier. As a result, the modulation techniques can be split in two types digital and analog modulations, often referred to as keying. The three components of a sinusoidal signal are amplitude, frequency, and phase, resulting in three main modulation methods. Amplitude shift keying, frequency-shift keying, and phase-shift keying are the three basic binary modulations shown in Fig 2.3. These three basic modulation schemes can be used to create a variety of modulation schemes.

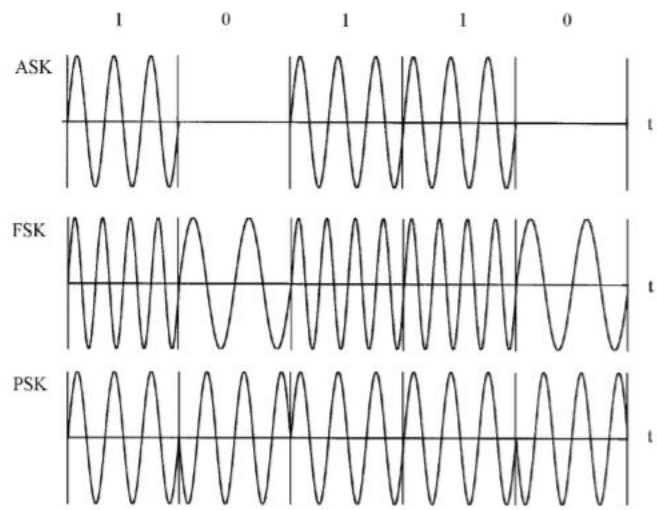

Fig 2.3: Modulation schemes for bandpass [8]

The conceptual criteria for modulation systems are high information transmission rate, narrow signal baud rate, low transmitting power, less error rate and low computation power. As a result, the modulation scheme should be carefully chosen, taking into account of the channel environment.

2.2: Wireless Channel:

Understanding of channel parameters is critical for optimal performance and the proper selection of modulation methods. A simplified digital communication model is depicted in Fig. 2.4. Three components make up the channel in this diagram. The transfer function of channel filter is the first component.

$$H(t) = H_T(t)H_C(t)H_R(t) \tag{2.1}$$

consists of the receiver, channel, and transmitter's transfer functions. Fading is represented by the second element, and the factor A(t) is usually complicated. The additive noise and interference term n(t) is the final factor.

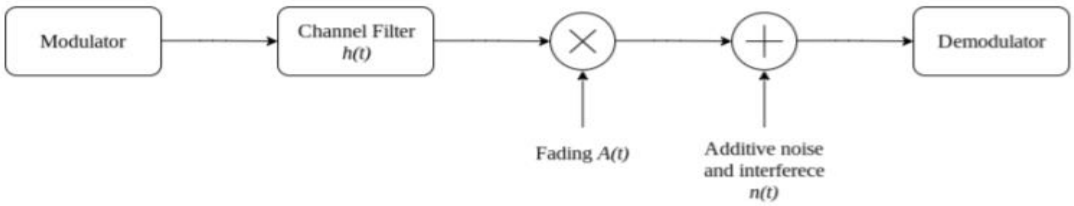

Fig 2.4: block diagram of simple modulation and demodulation [17]

The signal received at the demodulator might be expressed as:

$$r(t) = A(t)[s(t) * h(t)] + n(t). \tag{2.2}$$

For better real-world representation, the mathematical models are used to generate distinct signals for modulation categorization. As a result, this section introduces the most well-known channel models.

2.2.1: AWGN - Additive White Gaussian Noise channel:

The noise model (AWGN) is commonly utilized and is often regarded as a primary restriction in effective modulation categorization. It permits simulation of channels with considerable electronic noise produced by thermal agitation of electrons in an electrical wire at equilibrium. This channel's amplitude-frequency response is flat over an unbounded baud rate, and it's phase-frequency response is constant across all bandwidths. This channel doesn't fade the signal but only adds the passing signal s(t) to AWGN (n(t)):

$$r(t) = s(t) + n(t) \tag{2.3}$$

2.2.2: Fading Channel:

Slow and fast fading are the two types of fading. Slow fading, also known as shadowing, happens when a huge thing blocks the transferred signal. intervention among various types of the transferred signal causes fast fading. Attenuated copies of the original signal are created by diffraction, absorption, or reflection, and the time each version takes to reach the recipient varies slightly.

Carrier frequency shifting and signal bandwidth spreading generated by various Doppler shifts brought on by the movement of the transmitter and receiver.

Fading alters the characteristics of the transmitted signal. Other reasons of fading include inter-symbol interference, fluctuation in amplitude, and phase variation. The classifier must be strong in fading channels when performing modulation classification.

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2.3: The Receiver:

In this, the signal that is transferred goes through a same procedure in receiver as it does in the transmitter, but the order is reversed. The signal must first be demodulated before being transmitted to the channel and source decoders. If the user receives the signal as digital, it can be transferred to them. To acquire an analog signal from a digital signal, it must first be transmitted along a DAC that is digital to analog converter.

It is incorrect to presume that AWGN was the only factor that impacted the channel and that the transmitter and receiver are completely synced. Delays, phase and frequency changes, and distortions are typically present in the received signal. Despite timing distortion or phase jitter produced by asynchronicity and distortion, receiver must fix all the flaws to provide excellent detection. As a result, the receiver contains equalization and integration.

CHAPTER 3

METHODOLOGY FOR MODULATION CLASSIFICATION

It is critical to have an accurate classifier as part of a communication system. The demodulator will not be able to utilize the appropriate demodulation method if the categorization is incorrect, and the whole transmission will fail. The classifier is challenged by the multiple factors that affect the channel, such as AWGN, Doppler shift, fading and many others. They must be taken into account when constructing the classifier for actual applications. It's also vital to know a variety of modulation kinds, and it should be able to work with only a basic understanding of channel circumstances. Another factor to consider is the complexity, which influences both the hardware selections and the computation's processing time. As a result, a durable, adaptable, computationally efficient, and accurate classifier is essential for completing the signal transmission and recovering the collected message.

Currently, likelihood-based and feature-based classification techniques are used to categorize radio modulations. The novel categorization approach used in this thesis makes use of DL techniques. These 3 strategies are summarized in this chapter; other details in [9].

3.1: Likelihood-based approach:

This approach comprise-of two parts and is found on several compound assumption-testing issues. In the first, using observed signal samples, a probability is calculated for every modulation assumption. The generated likelihood functions can be tweaked to reduce computing complexity or make them work in non-cooperative situations. The likelihood functions of distinct modulation hypotheses are compared in the second phase to arrive at a classification choice.

This approach delivers the best classification performance. However, as the no of unknown parameters grows, it becomes more difficult to derive a precise analytical solution for the decision function. The intricacy of the classifier and its performance are also trade-offs [10].

3.2: Feature based approach:

A feature extraction and a classifier are the two major components of the feature-based technique. There are no definitive criteria for choosing the proper features, but they should be modulation-sensitive and being inconsiderate to noisy channels and varying SNR. The most prevalent features described in the literature are spectral, statistical, spectrum, and constellation shape features. Each feature has its own set of benefits and drawbacks. Although spectral characteristics have a modest level of complexity, they are susceptible to additive noise. Functions which use the third or higher power of a sample are susceptible to additive white gaussian noise and channels with one or more paths, as well as careful in discerning modulation methods like M-ary Phase Shift Keying and M-ary quadrature amplitude modulation. The computational complexity of cyclo-stationary features is high.[11].

Following the extraction of the features, all these sent to a categorizer, it frequently uses ML. Artificial Neural Networks, Support Vector Machines, and Decision trees are some of the most popular classification algorithms.

3.3: Novel Deep Learning Techniques:

DL categorization for modulation is relatively a new solution to the issue that has gotten a lot of attention in the last five years. This method differs in the way as source signal could get delivered straight to categorizer of a deep learning algorithm. No extraction of features is needed for this to work also doesn’t require any information about the signal's parameters. A large no of modulations could be handled by the categorizer without noticeably raising computing intricacy.

There are several DL architecture alternatives available for use in a variety of applications. Selecting or creating a proper design can be difficult because performance is dependent on a variety of parameters. The network's performance and size may be significantly impacted by hyper-parameters, which are factors that determine the structure of the network. Examples include the no of hidden units and layers, and others. However, once there are few available models because of transfer learning, it may tend to be fairly accessible and simply reclaimable. Transfer learning, a method that enables quicker training with greater accuracy on a smaller dataset than would be achievable if a model were built from scratch, uses variables from a saved network model (which was trained on a larger dataset) learnt on comparable data as a training starting point.

CHAPTER 4

DEEP LEARNING ARCHITECTURE

The extremely common architecture that is used now a days is convolutional neural networks (CNN) architecture [4,5]. This chapter discusses the architecture of CNN in detail.

4.1: Architecture 1 (Convolutional Neural Networks):

CNNs are algorithms that deal with the information that has a mesh-type structure. These could be considered as neural networks with at least one layer that uses convolution instead of standard matrix multiplication. CNN architectures are currently futuristic in most computer vision tasks and image information could be visualized as mesh of two-dimensional picture elements. As time-series information has a one-dimensional mesh-type structure, it is applicable to CNNs.

Convolution, in general, describes how the form of one function affects the structure of the other when applied to 2 outcomes with a real input. It is said to be defined as:

$$s(t) = x(t) * w(t) = \int_{-\infty}^{+\infty} x(\tau) w(t-\tau)\, d\tau, \qquad (4.1)$$

where w(t) represents for kernel, x(t) represents for input, and s(t) stands for feature map.

In machine learning (ML), the input information, along with the kernel, are commonly multidimensional, thus convolution is frequently utilized across multiple axes at once. Because flipping isn't necessary in machine learning. Instead of a convolutional process, the majority of NN packages employ cross-correlation.

$$S(i,j) = K(i) * I(j) = \sum_m \sum_n I(i+m, j+n) K(m,n). \qquad (4.2)$$

Three basic layers that make up CNN are fully connected layer, pooling layer and convolutional layer.

Only some of the source information points can be observed each time by the convolutional layer, which isn’t linked to all of them. The area's size is determined by the size of the convolutional kernel, which is a parameter matrix that has been optimized by the DL network. This allows the network to notice both high and low-level features. An activation function, such as a non-linear ReLu function, is then utilized to activate the extracted features.

The pooling layer helps decrease the source information size. The 2 most frequent ways are mean and max pooling, in which window’s max rate is used or the mean rate is calculated. Pooling layer has no parameters and assists in the reduction of the final model's size. This can help to prevent overfitting and lower the amount of memory required for processing.

At the end of the network, properties are translated into labels using the dense (completely connected) layer. These layers have neurons that are totally linked to the layer above them. The final dense layer in a categorization task is usually triggered by a softmax activation function, that allocates the information to the most accurately anticipated class.

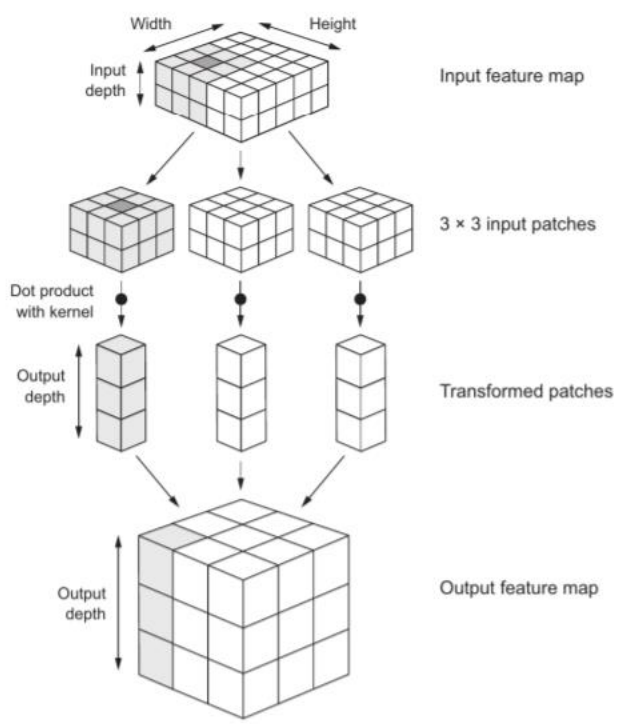


Fig:4.1: Working principle of convolution [12]

4.2: Design:

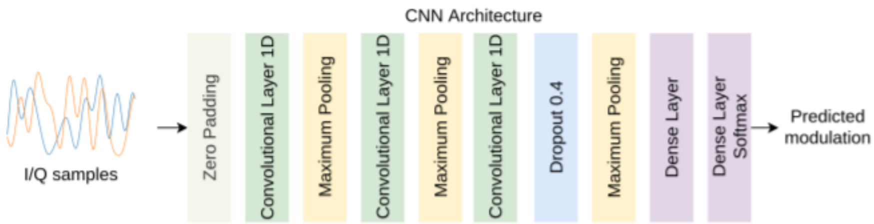
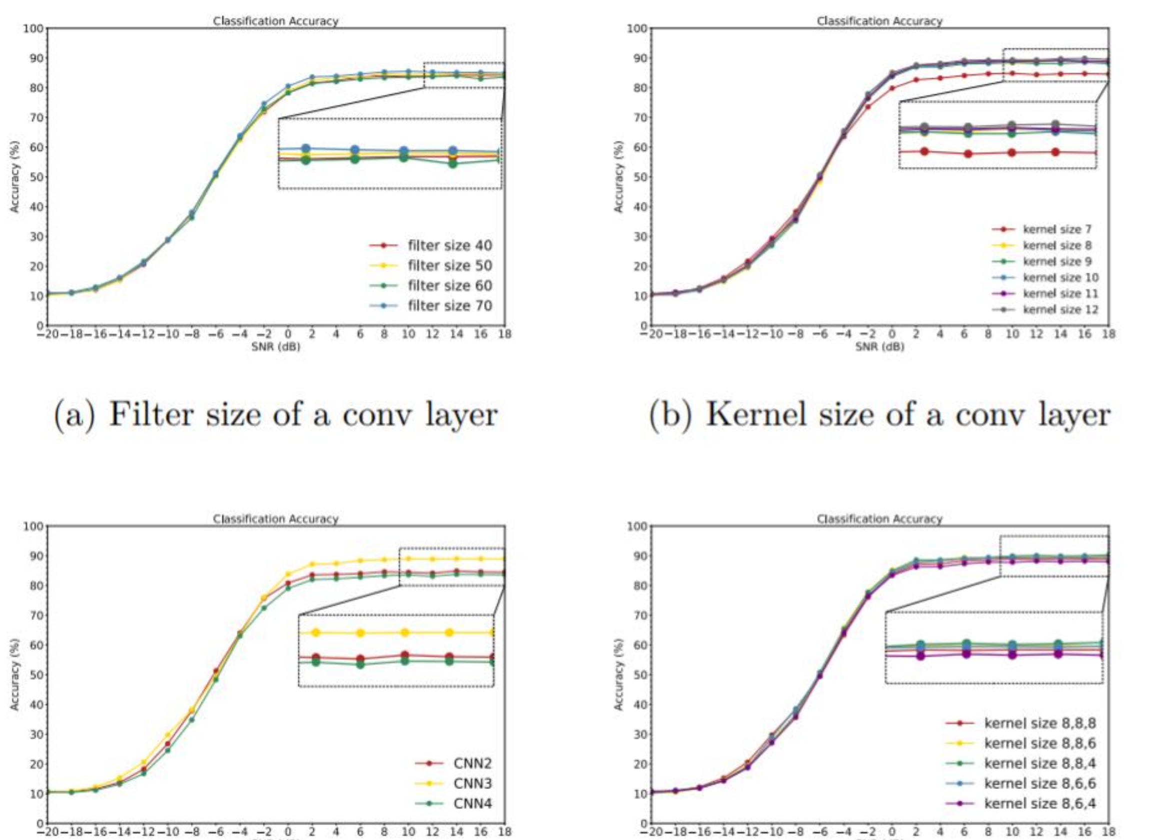


Fig 4.2: CNN Architecture [13]

The architecture is substantially simpler than other CNNs used in machine vision, like ResNet. However, it appears that modulation classification is not as difficult for neural networks as classification of images, and that even with simpler designs, the networks can identify adequate features.



(a) Filter size of a conv layer

(b) Kernel size of a conv layer

(c) Varying numbers of conv layers

(d) Varying kernel sizes of conv layers

Fig 4.3: CNN Parameter Tuning

For higher kernel and filter sizes, the achievement variation in between the filter and kernel sizes in Fig. 4.3a and 4.3b isn't substantial. Because those hyper-parameters might have a big impact on the last no of parameters in the design, I went with kernel sizes of 8, 8, and 4 and a filter size of 40, as shown in Fig. 4.2d. At last, as shown in Fig. 4.2c, the best option for the problem is 3 convolutional layers.

Layer	**Arguments**	**Output Shape**
Input	Shape (128,2)	128x2
Zero Padding 1D	Padding 4	136x40
Convolution 1D	Filters 40, Kernels 8, ReLu	129x40
Max Pooling 1D	Pool size 2	64x40
Convolution 1D	Filters 40, Kernels 8, ReLu	57x40
Max Pooling 1D	Pool size 2	28x40
Conv	Filters 40, Kernels 4, ReLu	25x40
Dropout	Rate 0.6	25x40
Max Pooling 1D	Pool size 2	12x40
Flaten	-	600
Dense	Units 65, SeLu	65
Dense	Units N1, Softmax	N

Table 4.4: Architecture of CNN

The final architecture mainly contains three of one dimensional convolutional layers. A tensor of outputs in these layers are produced when the kernel is convolved across one spatial dimension. A rectified linear activation function (ReLu) is used to activate the layers, providing them with non-linearity.

The layers of max pooling under sample the sequence length by taking the max result within a spatial frame, the length of which is determined by the pooling size. To avoid overfitting, a dropout layer is added, and the network is completed with two completely linked layers. The Softmax activation function activates the final dense layer.

Table 4.4 provides an overview of the parameters that are exactly chosen for the network. There are 73,730 parameters overall.

4.3: CLDNN:

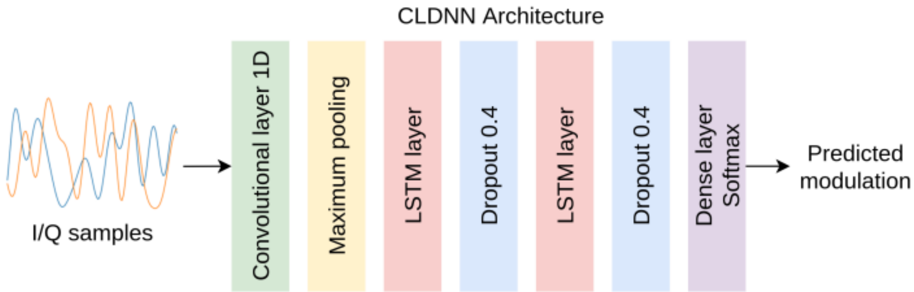


Fig: 4.5: CLDNN Architecture Layout [13]

CLDNN is the next suggested deep learning architecture. The convolutional-recurrent network combo combines sectional feature extraction from long-term memory consistency from the LSTM layers and the convolutional layer. 1 LSTM layer and 3 convolutional layers were utilized in CLDNN architectures in [4] and [23]. Nevertheless, the architecture suggested for this report is made up of maximum pooling and convolutional layer, after which there are two Long Short-Term Memory layers along with drop-out layers to avoid overfitting, because it's possible to achieve good outcomes in the manner. In the final layer a dense layer is activated with the use of a Softmax function once more. Fig. 4.5 depicts the CLDNN architecture's overall layout, and Table 4.6 lists the arguments for the various layers that were used. There are 105,546 parameters generated by this architecture.

Layers	Arguments	Output Shape
Input	Shape (128,2)	128x2
Convolution 1Dimension	Filters 40, Kernels 8, ReLu	129x40
Max Pooling 1Dimension	Pool size 2	64x40
LSTM	Filters 40, Kernels 8, ReLu	57x40
Dropout	Pool size 2	28x40
LSTM	Filters 40, Kernels 4, ReLu	25x40
Dropout	Rate 0.6	25x40
Flaten	-	3480
Dense	Units N1, Softmax	N

Table 4.6: Architecture of CLDNN

4.4: Visualization of Layers:

DL designs are sometimes referred to be "black boxes" since we feed information into them and acquire an answer to our issues in return, yet this procedure in the middle is a mystery to everyone. The information is sent along the layers, and network tries to uncover useful characteristics that may or may not be obvious to us. We can, at the very least, see what happens to the information like it passes along the prepared network. This may not address all of your questions concerning the network's procedure of learning, but might help us understand concept.

This visual representation depicts layer and feature map activations. Data activates particular elements of the filters or gates as it passes through the levels of the network. We create a feature map that identifies the features that are pertinent for each filter by mapping activations like these onto the series that generated them.

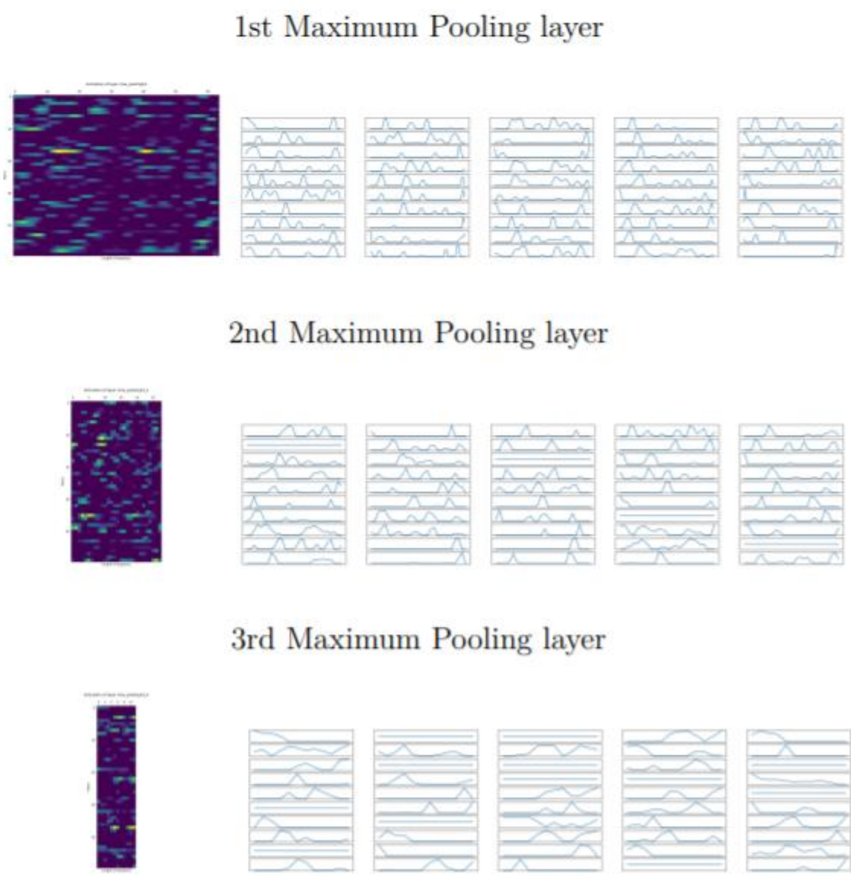


Figure 4.7: Feature and Activation plots on right and left respectively of CNN layers

CHAPTER 5

DATASET

In deep learning, choosing an appropriate DL approach and a good-quality dataset are both necessary for developing a reliable final model for a particular job. The learned characteristics that were taken from the training source data impact how well the trained model performs, therefore it's possible that it won't generalise well if some actual-world scenarios aren't included in the dataset.

Among several blatantly accessible datasets, the most popular datasets are of RadioML datasets. The creators of the RadioML datasets claim that because communication system steps are frequently synthetic and deterministic, a synthetical dataset can be used. These data sets are either collected experimentally or artificially.

When generating a robust dataset, we should take note that modern communication systems are adaptable also contains various arrangement positions and factors. due to the non-availability of publicly available, the following sections detail the synthetic and experimental datasets that the systems in this report were developed on.

5.1: RadioML datasets:

The DeepSig firm released their first datasets for modulation classification in 2016 [14]. They also published a report in which they illustrated the application of convolutional neural networks to the AMC. Although this was not the first study on the subject to be published, it is frequently mentioned since it made the AMC job more accessible to others by making the datasets publicly available.

GNU Radio software is used to create these signals in the datasets and are synthetic. To represent actual circumstances, center frequency offset, sample rate offsets, channel mode blocks, AWGN and selective fading were included. In order to further utilise the data in the field of machine learning, the information was measured to unity energy as a last step.

2x128 vectors of in-phase and quadrature signals (I/Q) are utilised to represent the information. The SNRs were designed for range from -20 dB to 18 dB. The versions of RadioML2016 contain analogue and digital modulations like Binary Phase Shift

Keying, Quadrature Phase Shift Keying, 8 Phase Shift Keying, Quadrature Amplitude Modulation 16, Quadrature Amplitude Modulation 64, Continuous Phase Frequency Shift Keying, Gaussian frequency-shift keying, Pulse Amplitude Modulation 4, Amplitude modulation- single sideband modulation, and Wide Band FM Modulation. In this thesis, 10a and 10b were employed. Version 10a has 220,000 samples, whereas version 10b contains 1,200,000 samples.

5.2: Migou-Mod dataset:

Signals that are calculated wirelessly can be obtained in the Migou-Mod Dataset [15]. USRP B210 was used to create the transmitter, which was linked to the PC running GNU Radio software. Just like RadioML there are 11 modulations in this dataset. The authors passed down the similar set of instructions and sources of information as developers of the RadioML dataset. On the receiver side, they employed a MIGOU platform to retrieve the signals. The measurements for this dataset were taken at distances of 1 and 6 meters in an office setting. The average SNRs for these frequencies are 36 dB and 21 dB, respectively. The information is constituted as 2x128 I/Q vectors, yielding 8.8 million samples in total.

CHAPTER 6

RESULTS

This section provides outcomes of the above discussed architecture. To make comparisons easier, they are displayed as confusion matrices (CMs). The x-axis displays the predicted labels, while the y-axis displays the truth labels. The efficiency of the categorization issue is assessed for N classes using the confusion matrix. Everything outside of the major diagonal was misclassified, allowing us to identify the classes that were misclassified the most frequently. Groups on the major diagonal of the CM were correctly identified. The following CMs are blue in tone, and the deeper the tint, the more frequently the categorization predictions for the specified class were made. Each matrix cell has the appropriate percentage marked on it for greater accuracy.

6.1: RadioML dataset:

This set of results is based on the RadioML 2016. Datasets 10a and 10b. note that, the only difference between both datasets is their size: the 10a variant has 2,25,000 samples of the signal whereas in 10b variant there are 12 lakh samples. When training the designs on 10a and 10b sets, the sample size was only hyper-parameter that was altered. The 10a version had a value of 128 while the 10b version had a value of 256, the larger 10b variation made training more quickly possible by raising the number. When we combine the outcomes of the 2 sample sets, we can observe how the dataset size affects the results.

CNN Architecture:

Figures below represents the results of CNN architecture. Incorrect classification is high for lower SNRs as shown in fig 6.1 and 6.5. Although the overall accuracy is approximately 50%, we can observe that some of the classifiers were able to recognize correct modulation. For SNR = 18dB, we notice a significant improvement in classification, with the majority of modulation classes correctly recognized. Although there is still some confusion between Quadrature Phase Shift Keying and 8 level Phase Shift Keying, both datasets analog signal categorization has enhanced slightly. We can observe how the size of the dataset could affect the categorization by comparing the Quadrature Amplitude Modulation scheme categorization for the two datasets in Figure 6.3 and 6.7.

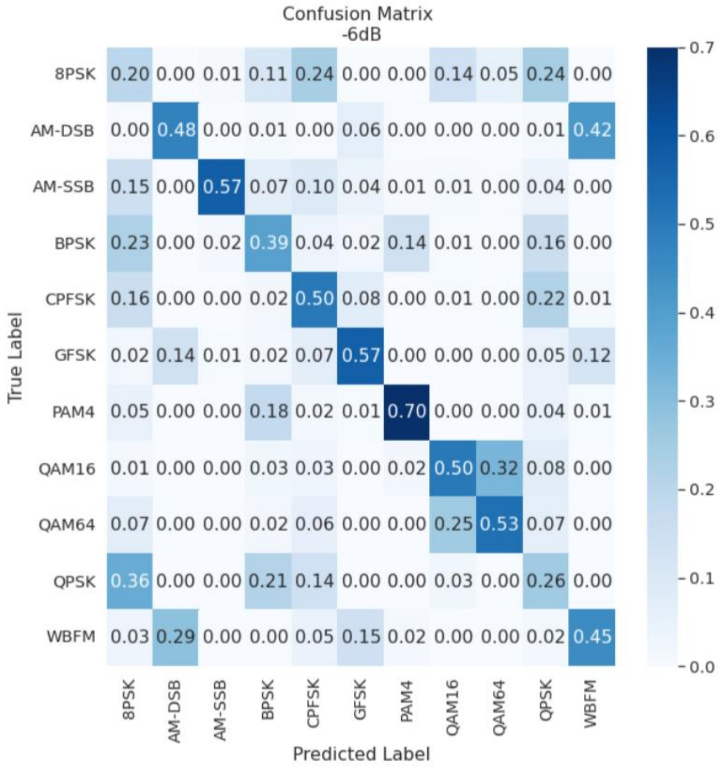


Fig: 6.1: Confusion matrix at SNR = -6db (10a)

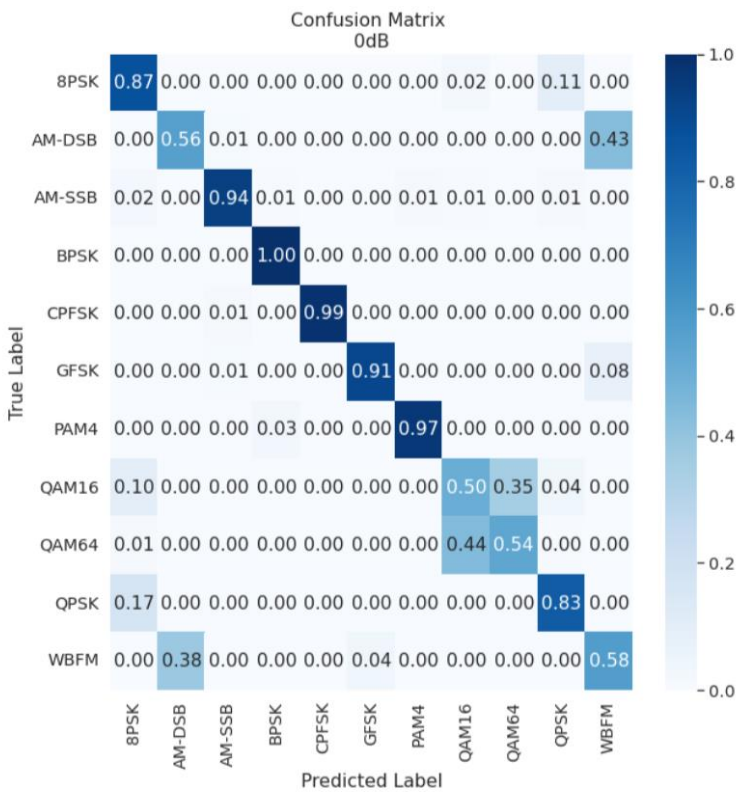


Fig:6.2: Confusion matrix at SNR = 0db (10a)

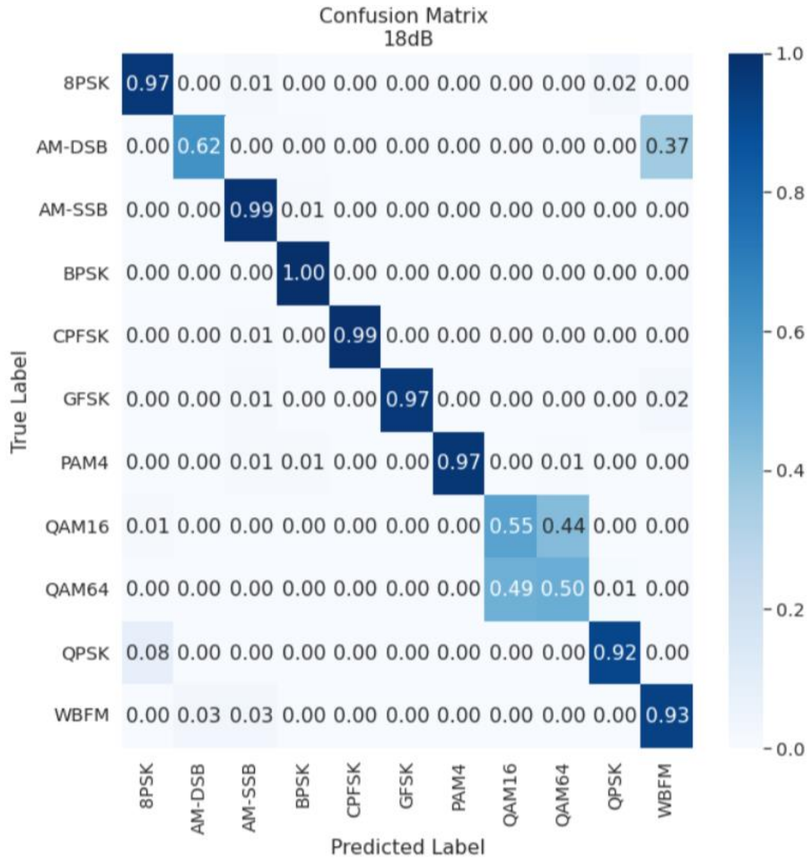
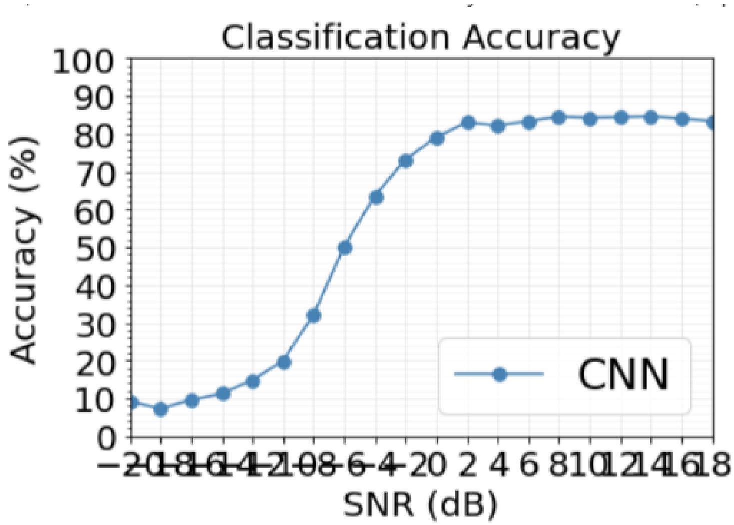


Fig:6.3: Confusion matrix at SNR = 18db (10a)




```
array([0.09136736, 0.07277138, 0.09537914, 0.11246376, 0.14812499,
       0.19880952, 0.32153752, 0.50242424, 0.63593102, 0.73204589,
       0.79098111, 0.83003706, 0.82166767, 0.83353806, 0.8454318 ,
       0.84264266, 0.84409255, 0.84629297, 0.84056199, 0.8336252 ])
```

Fig: 6.4: Accuracy CNN (10a)

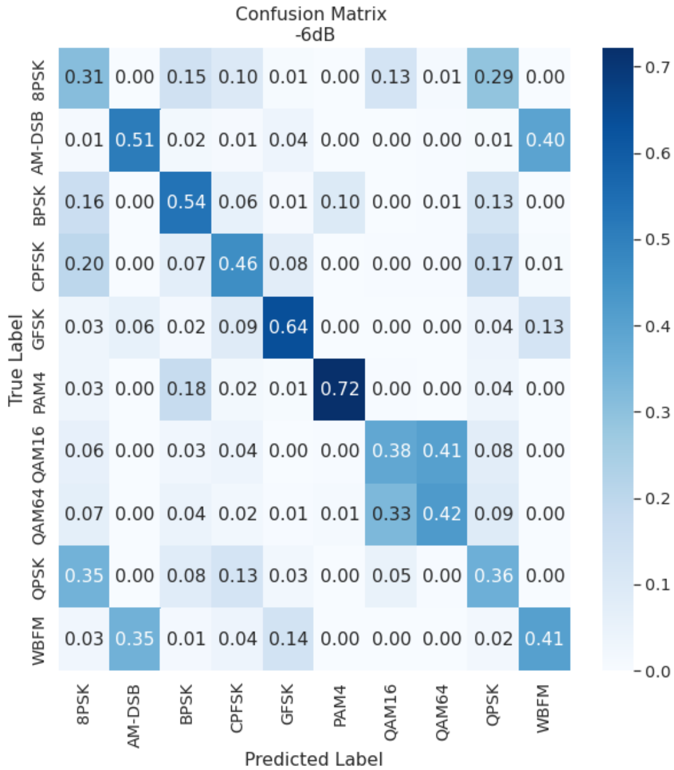


Fig:6.5: Confusion matrix at SNR= -6db (10b)

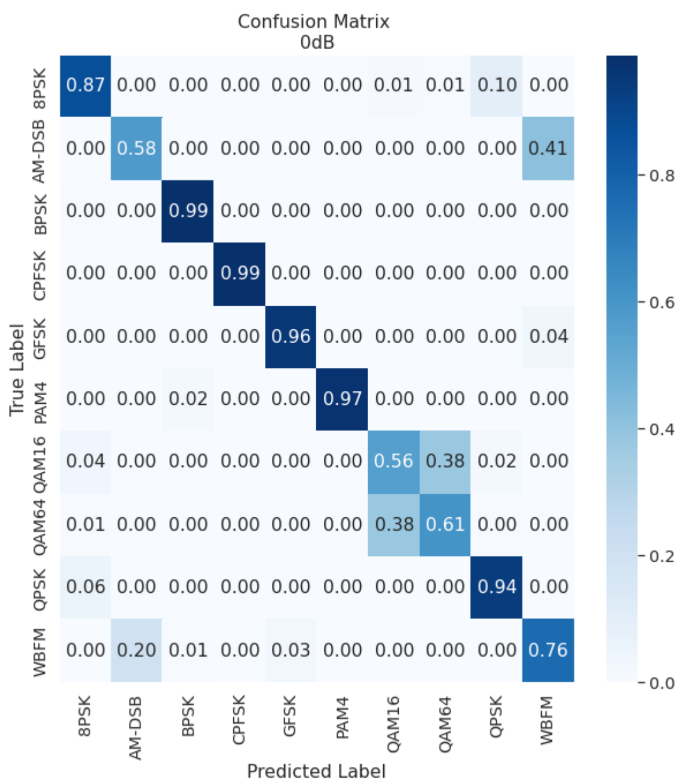


Fig:6.6: Confusion Matrix at SNR = 0db (10b)

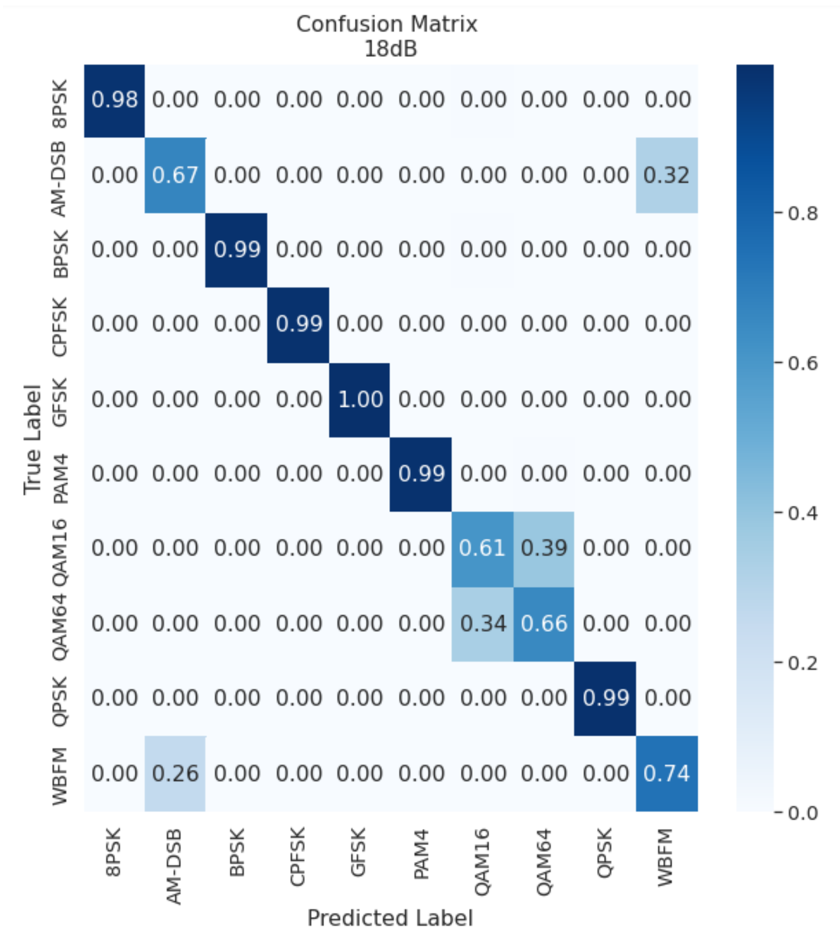
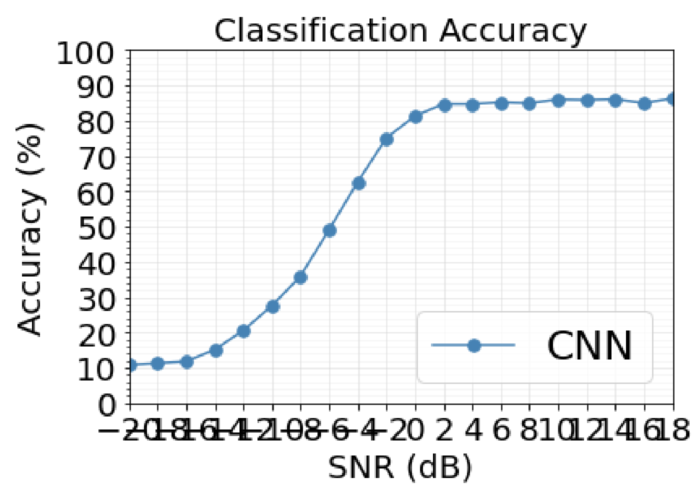


Fig:6.7: Confusion Matrix at SNR = 18db (10b)




```
array([0.10814668, 0.11297303, 0.11788168, 0.15118599, 0.20538385,
       0.27561602, 0.35883847, 0.49095148, 0.62602162, 0.7506634 ,
       0.81328124, 0.84736139, 0.84715575, 0.85217297, 0.84961909,
       0.86004442, 0.85877353, 0.86080873, 0.85003406, 0.86286944])
```

Fig:6.8: Accuracy CNN (10b)

For Quadrature Amplitude Modulation schemes, the DL algorithm trained on the 10b version depicted in 6.6, which has six and a half times more samples for each level of SNR and modulation, was able to achieve an accuracy of about 80%. Only half of the samples were correctly classified by the DL algorithm which used 10a dataset which contains 2,20,000 samples only to train as given in the 6.2. The dataset's developers used voice recordings that included speech pauses. Because signal sample size is so short, some of them are just the speech pauses. The network learns to categorize these events as Wide Band FM modulation because the carrier frequency, which is constant across all analogue modulations, is the only information present in the signal. The single big recognized difference as the SNR level is increased is the confusion of Wide Band FM for Amplitude Modulation-DSB. It's caused by the data that's used to generate analog modulations. Even with greater SNRs, there is still uncertainty regarding the QAM schemes, and the network finds it tough to distinguish between them. For this instance, a large dataset and additional training data did help the CNN network.

CLDNN Architecture: For RadioML (10a):

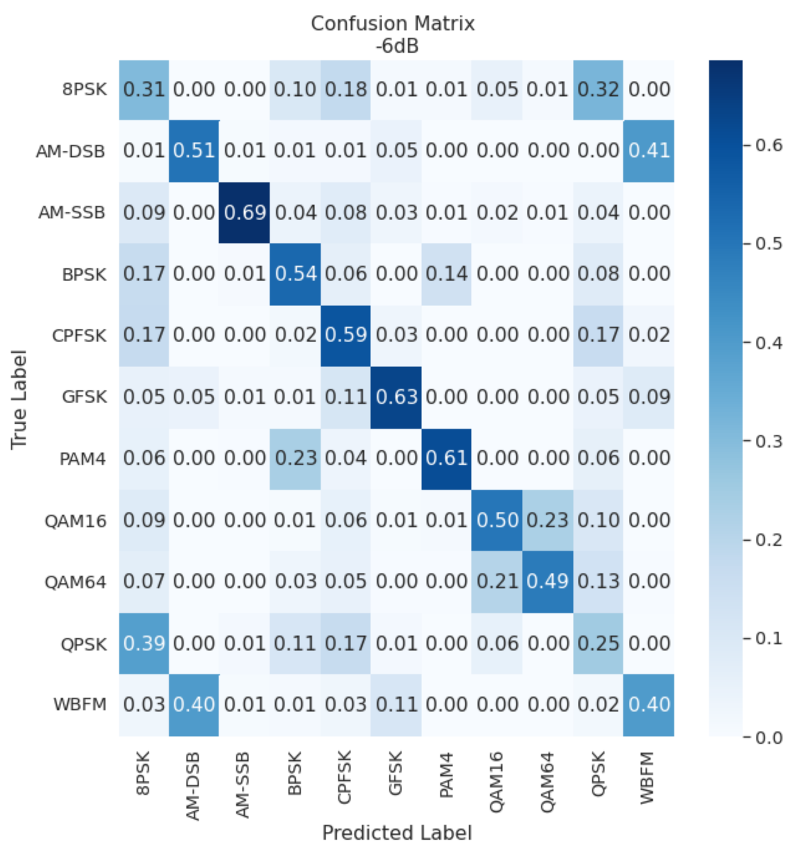


Fig: 6.9: Confusion matrix at SNR = -6db (10a)

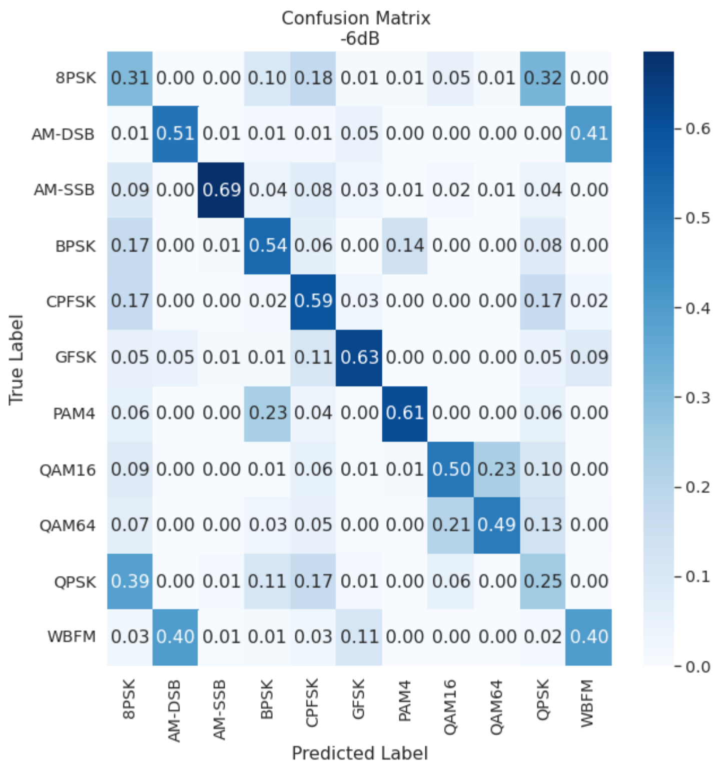


Fig: 6.10: Confusion matrix at SNR = 0db (10a)

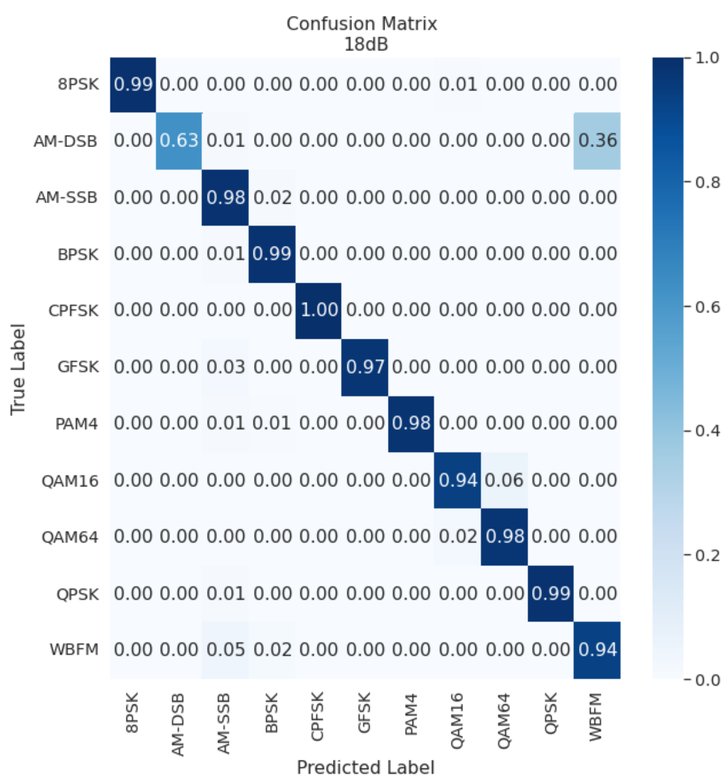
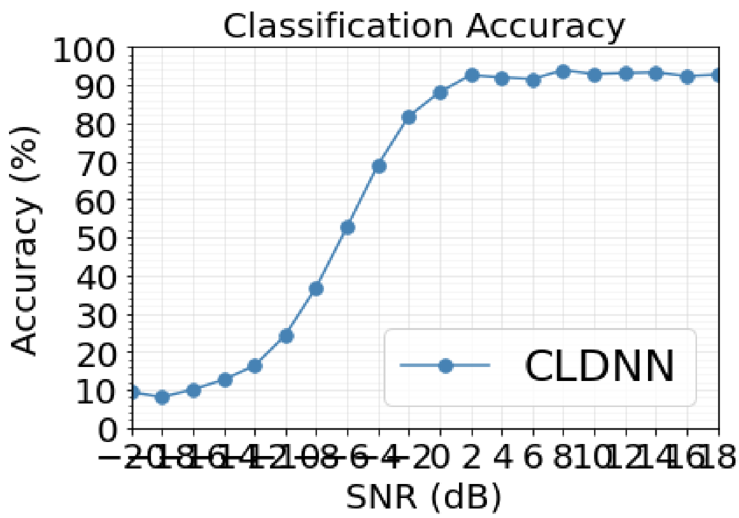


Fig: 6.11: Confusion matrix at SNR = 18db (10a)




```
array([0.09388784, 0.08065494, 0.1007109 , 0.12637681, 0.16312499,
       0.24285714, 0.3685174 , 0.52666664, 0.68947053, 0.81774288,
       0.88117003, 0.9264524 , 0.92026782, 0.91584766, 0.93929911,
       0.92912912, 0.93179047, 0.93369502, 0.92364079, 0.92761236])
```

Fig: 6.12: Accuracy CLDNN (10a)

CLDNN Architecture: For RadioML (10b):

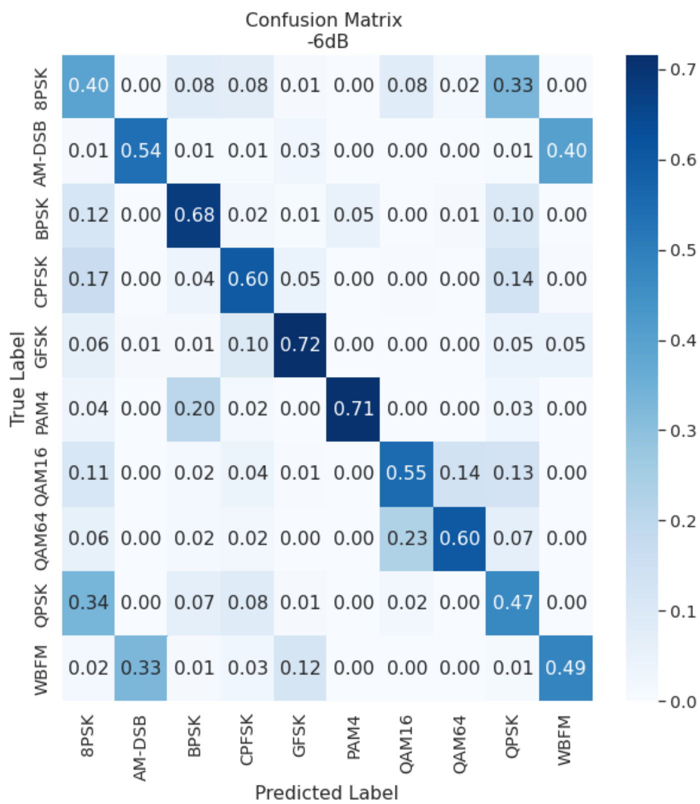


Fig: 6.13: Confusion matrix at SNR = -6db (10b)

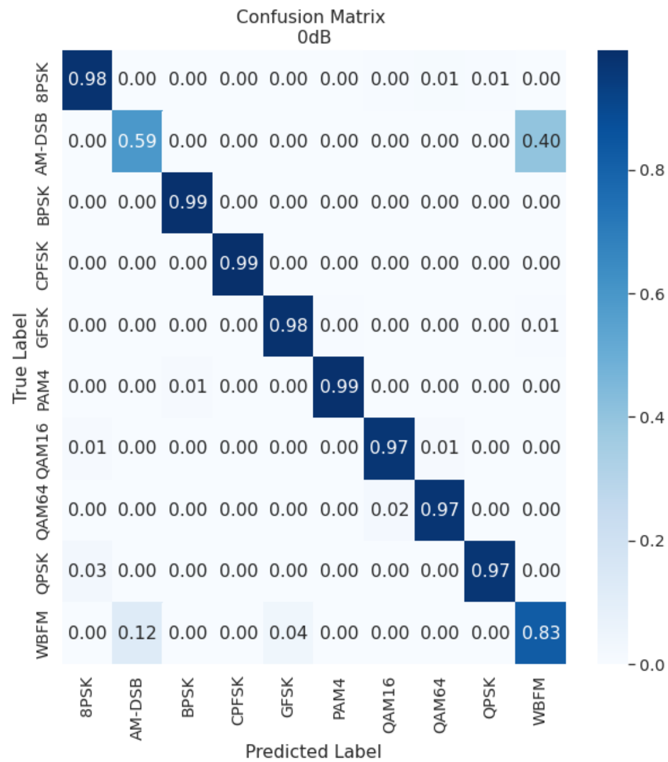


Fig: 6.14: Confusion matrix at SNR = 0db (10b)

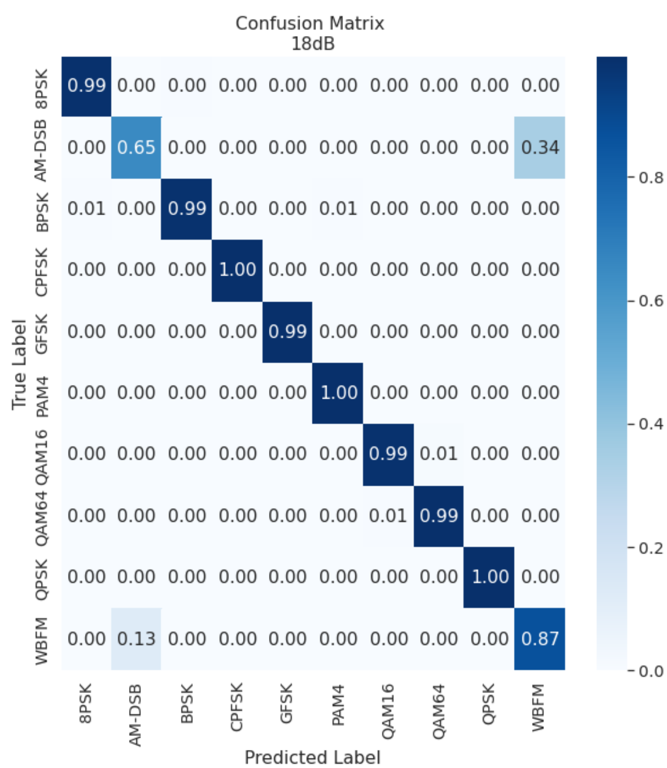
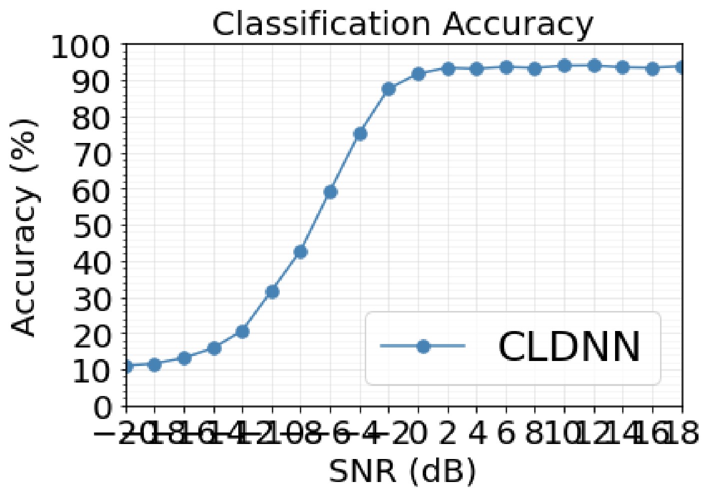


Fig: 6.15: Confusion matrix at SNR = 18db (10b)




```
array([0.11012297, 0.11552547, 0.13139819, 0.15783639, 0.20638086,
       0.31620026, 0.42762503, 0.59253913, 0.75127017, 0.87582928,
       0.91696429, 0.93397909, 0.93131471, 0.93667692, 0.93353206,
       0.93984461, 0.94046551, 0.93545878, 0.93399227, 0.93817234])
```

Fig: 6.16: Accuracy CLDNN (10b)

Above figures represent the confusion matrices for CLDNN architecture for both 10a and 10b datasets. At first, the confusion matrices at SNR level -6db seem comparable to the results of Confusion matrices from CNN. But if we look closely, we can see that the QAMs are performing better. Out of two datasets, the development is most noticeable for the larger dataset 10b in figure 6.13, where the categorization accuracy is increased by twenty percent as collated to Convolutional Networks in figure 6.5

There is also more development at the high Signal to Noise Ratio levels. The classification efficiency of Quadrature Amplitude Modulation’s is increased by up to 85 percent which is around 34 percent more development contrast to that of CNN result. At SNR level 0db for 10b dataset version the QAMs achieved accuracy over 96% and the architecture was able to increase the WBFM's accuracy by 10% as shown in fig 6.14

In this architecture, the blend of both convolutional and recurrent layers seem to be appropriate for the problem. In comparison to the Convolutional Neural Networks, the architecture CLDNN was better proficient to identify features that were appropriate for the various classes, particularly the QAMs. Although the precision for the smaller dataset remains slightly low, it’s no longer that severe. However, computing process is slowed due to recurrent layers and training time is two times longer per epoch.

CHAPTER 7

CONCLUSION

The goal of this thesis is to apply deep learning methods to develop radio modulation classifiers. The deep learning classifiers can function directly with the received data, without the need for any prior knowledge or feature extractions. They could also be trained to identify a wide variety of modulation types without increasing computational complexity significantly. They're easy to upgrade to carry more signals or modulation classes from other surroundings.

The architecture that is proposed in this report show that a proper hyper-tuned architecture, even with a reduced number of variables can yield better outcomes. The above are the results with the CNN and CLDNN architecture. The recommended CLDNN architecture was successful in matching or outperforming the majority of past models. When compared to the architectures from studies [3] and [4], this has also decreased parameters by up to 20 and 50 times, respectively. The synthetic signals can imitate a variety of channel impairments, but real-world data collected in a non-laboratory setting is required. The absence of such a representative dataset is the most significant limitation of the thesis, as it is critical for the reliability of the categorizer in actual life applications. Overall, in Modulation classification the DL approaches show great potential that can be used. Robust datasets must be used to train DL classifiers. Transfer learning has the potential to make this approach easily accessible and re-usable to others. Future work can be focused on getting a real-life dataset which is much larger than the ones available to increase the accuracy at lower SNR levels.

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