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"DEEP LEARNING BASED MODULATION CLASSIFICATION"

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ABSTRACT

The ability to classify various types of signal modulations in radio transmissions is an important task for applications in defense, networking and communication areas. This process was traditionally performed manually by human analysis. Recent advances have shown that deep learning methods apply to this feasible task. But existing recognition networks are complex, with high computational requirements and low precision for some types of modulation and in environments not included. We have developed a robust high-frequency signal classifier with a hybrid approach that uses images derived from the signal constellation and spectrogram data in combination with an efficient neural folding network. Compared to the latest generation deep learning classifier, our system achieves better accuracy with lower computational requirements. We conduct an in-depth study on the performance of deep learning-based radio signal classification for radio communications signals.

Keywords: signal modulation, radio transmission, deep learning, automatic modulation classification,

CHAPTER 1
INTRODUCTION

1.1. PREAMBLE

Rapidly Understanding and labeling radio spectrum autonomously is an important enabler for spectrum interference, radio error detection, dynamic spectrum access, opportunistic mesh networks, and numerous regulatory applications and defense applications. Build complex high-quality RF information, to become accurate and precise labels that are carefully made and work together and transmitted, today, today is a critical component in numerous radio and communication learning systems. For many years, radio signal classification and modulation detection were achieved by handcraft specialized feature extractors carefully crafted for specific signal types and the properties and compact decision limits derived from them using analytically derived decision limits or statistically learned limits within low-dimensional feature spaces. In the last five years, there have been rapid failures due to improved architectures, algorithms and optimization techniques for neural networks known as deep learning (DL). DL recently replaced the state of art in computer learning (ML) in computer, voice and natural language processing; In both areas, characteristics engineering and preprocessing were once important issues that allowed intelligently designed extractors and transformations to extract relevant information in a manageable representation with reduced dimensions, from which labels or decisions could be easily learned using tools. As a support Vector machines or decision trees. These widespread end functions were the conversion of the invariant function (SIFT) [9], the word bag [8], the Cepstral coefficients Mel-Frequency Components [1] and others who were based on a few years ago, but they will no longer be for the performance of the Technology needs. The learning capacity of features has increased the learning capacity of characteristics directly to the high raw dimension data based on high levels due to the new learning capacity. Large neuronal network models with high number of parameter numbers. This was possible thanks to the combination of possible Strong regularization techniques [18], [21], greatly improved to face the decrease in Stochastic gradient (SGD) [15], [16], low-cost and high-performance graphic processing power and combination of key innovations in the architecture of neuronal networks, such as fundamental neural networks [5] and equal linear axes [13]. It was not until Alex Net [14] that many of these techniques were used together to increase the size of the practical model, the number of parameters and the target data set, as well as the complexity of the tasks that directly perform the learning, by several orders of magnitude. state-of-the-art images. The trend in ML has been relentless to provide rigid, simplified analysis functions and approximate models with more accurate, high quality freedom models (DOF) derived from the data they used. Learning characteristics from one end to the other. This trend has been demonstrated in the areas of vision, word processing and speech, but until recently has not been fully applied or fully implemented in radio time series data sets. We have shown in [30], [32] that these methods can easily be applied to simulated radio time series sample data to classify emitter types with excellent performance and to obtain equivalent accuracies that are many times more sensitive than the best methods.

Existing practices using features classifiers at higher levels. Moments of order introduced, and one in the in-depth analysis of many practical technical design and system parameters that affect the performance and accuracy of the radio signal classifier.

BACKGROUND

Wireless networks are characterized by various forms of shared communication due to network disturbances (other network users), network disturbances (other communication systems), Jammers, channel effects (such loss of route, fading, multipath and Doppler effects).In order to support dynamic spectrum access (DSA), network users should feel the spectrum and the hidden interference sources in Spectrum Dynamics. Machine Learning offers automated funds for newly created signals. Supported by recent computational and algorithmic advances, deep learning holds promise to extract and operate in latent spectrum data representations that conventional automatic learning algorithms have not achieved.

In particular, through deep learning, signals can be classified effectively depending on their types of modulation. Previous studies have assumed that the types of signals are known, remain unchanged and have no effects of interference. The assumptions are generally not valid in a realistic wireless network.

1) Signal types change over time.

2) Some signal types are unknown, and there is no training data for those signals available.

3) The signals are potentially spoofed, e.g., a smart jammer replay received signals from other users thereby hiding.

4) The signals overlap each other due to the simultaneous transfers of different signal types. It is essential to contain these four realistic cases.

In the construction of the RF signal classifier, so that its results can be used practically in a DSA protocol. We consider a classifier of wireless signals that classify signals based on modulation types in inactive users within the network (as a secondary user), users outside the network (e.g., primary users) and blockers). With the results of the signal classification, users of the network have time slots for collision-free programming in a distributed environment, and share the spectrum with each other and protect user transfers outside the network and avoid Interference of blockers.

Assuming that different types of signals use different modulations, we present a Convolutional Neural Network (CNN) that classifies the received I/Q samples as idle, on-network, interference, or off-network signals. We start with the simple base scenario that all signal types (i.e., modulations) are fixed and known (so training data is available) and there are no overlapping signals (i.e., signals are already separated). The average accuracy across all signal-to-noise ratios (SNR) is 0.934. Next, we extended the signal classifier to work in a realistic wireless network.

OBJECTIVE

Our objective is to develop a model to investigate the value of employing deep learning for the task of wireless signal modulation classification.

In this work we are trying to develop a deep network which will prove efficient for automatic modulation classification (AMC).

We will first train a very basic CNN record its performance and then we will develop a deeper network and train it followed by its testing.

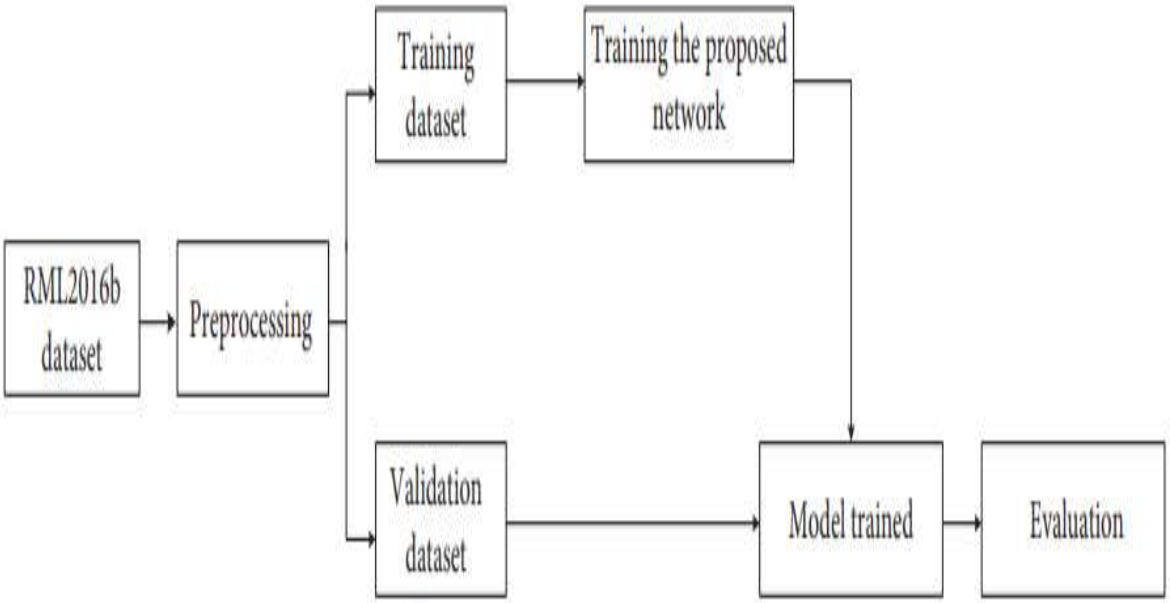


Fig 1: Workflow of System

We will evaluate the performance of our model on the testing data where the metrics to measure the performance will be accuracy, confusion matrix, classification report, f1 score.

Convolutional Neural Network

Convolutional neural networks (CNN, or ConvNet) are a category of deep high-frequency neural networks commonly used in image analysis. CNNs use a type of multi-layer perceptron designed to require minimal processing. Spatial Invariant Network based on Shift Invariant or Shared Structure (SIANN) - In terms of structure and symbols of various interpretations, convolutional networks are inspired by the biological process of connection patterns between neurons, such as the visual field of animal tissue. it was done. Cortical neurons respond individually Because the receptor fields of different neurons are intertwined to cover the entire visual field, the CNN is pre-data-composed compared to other algorithms compared to other algorithm networks. It requires less processing. Knowledge before reading the field of view and this independence functional design effort of human e are great benefits. There is an app for photos and videos recognition, recommender systems and natural language processing.

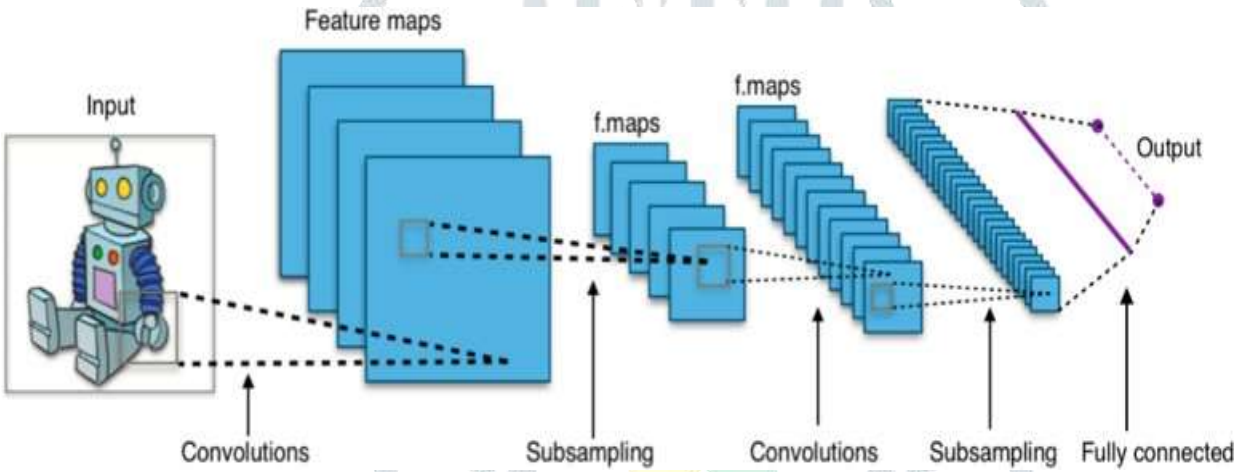
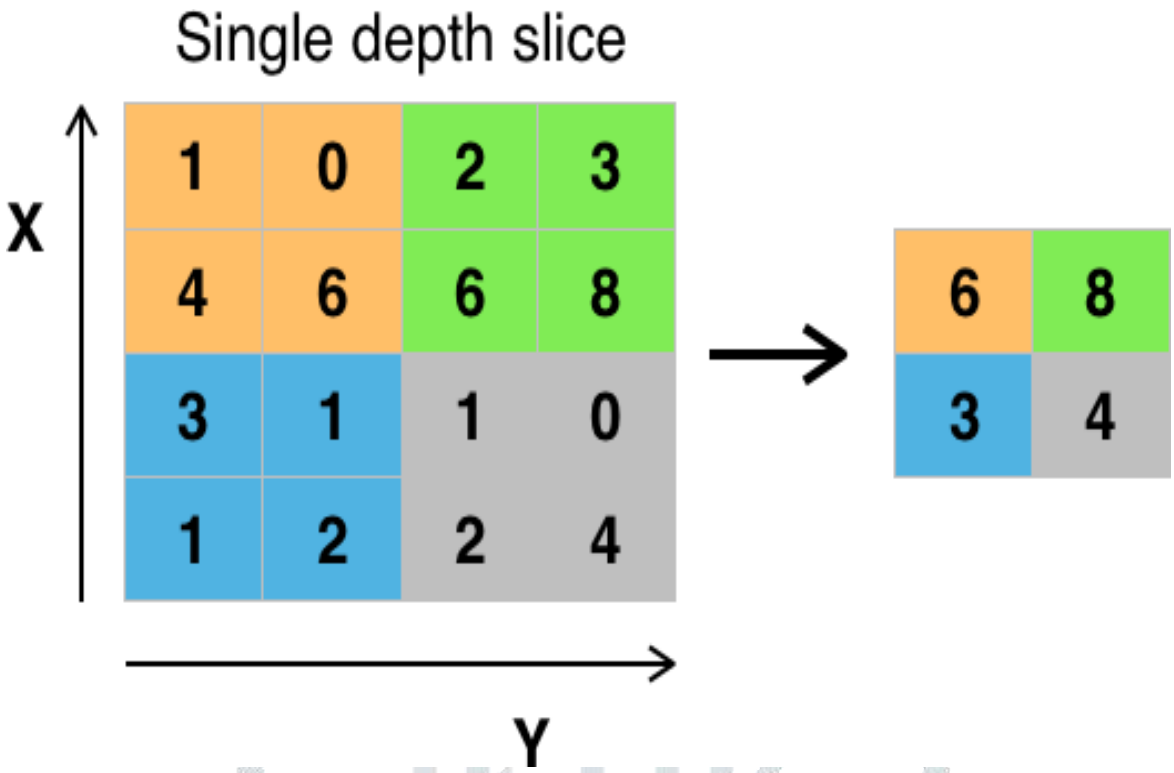


Fig2: Typical CNN Architecture

The CNN architecture of the neural network explicitly assumes that the input is an image so that you can encode certain properties into the architecture. This makes the implementation of forward functions more efficient and significantly reduces the number of parameters in the network. Layer description with the convolutional neural network described below.

• Convolutional layer: Convolution is the core building block of a convolutional network, doing most of the computationally difficult tasks. Three metadata (depth, stride and padding)

• Max Pooling Layer: Max pooling is a sample-based discretization process. Max pooling is done by applying a max filter to (usually) non-overlapping sub regions of the initial representation.



- Average Pooling Layer: Average pooling layer reduces the variance and complexity in the data. It also performs down-sampling by dividing the input into rectangular pooling regions and computing the average values of each region. The Output Size of an Average-Pooling layer is:
- Concat Layer: The Concat layer connects its multiple input blobs to output blob.
- Dropout Layer: A dropout layer randomly sets the input elements to zero with a given probability. The CNN's concatenation (FC) layer represents a feature vector for the input. This feature vector holds the information that is important to the input.
- Fully Connected Layer: The fully connected (FC) layer in the CNN represents the feature vector for the input. This feature vector holds information that is vital to the input.
- Max Pooling: Maximum pooling is a sample-based discrete process. Maximum pooling is done by applying a maximum filter. These are (typically)non-overlapping subareas.

2.2

1.2. THESIS LAYOUT

This thesis includes introduction of Deep Learning Based Automatic Modulation Classification, literature review and brief description about the methodology used for the System.

- Chapter 2: Includes the literature survey of previous works done in this field.
- Chapter 3: Explains the topics related to Deep Learning Based Automatic Modulation Classification.
- Chapter 4: Described the Design and Implementation of Deep Learning Based Automatic Modulation Classification.
- Chapter 5: This chapter explained screenshots with their results.
- Chapter 6: Conclusion of the dissertation has been made. Also explain future aspect of the dissertation.

CHAPTER 2
LITERATURE SURVEY AND PROPOSED METHODOLOGY

2.1. PREAMBLE

Nowadays respect to the emergence of multiple standards and innovative technologies for wireless communication, wherein radio signal should be encoded by a pre-defined modulation scheme according to the specification of transmission channel, spectrum analysis through the models of signal classification and modulation recognition plays a vital role in massive wireless communication systems like fifth generation (5G) . Fundamentally, modulation recognition is the task of classifying the modulation type of a received radio signal, which is treated as a multi-class decision problem. With The increasing number of advanced modulation algorithms, the high recognition accuracy of modulation type is of great importance in noise and multipath fading conditions. By Means of artificial intelligence (AI) algorithms , automatic modulation classification (AMC) is taken into account as a potential solution of efficient spectrum management. Most of the previous AMC works are typically categorized into the likelihood-based and feature-based groups.

While the likelihood-based methods waste an expensive computational capacity for unknown parameter estimation of classification models, the feature-based approaches are mostly influenced by the experience and knowledge of signal feature engineering. The feature-based methods are commonly deployed for many wireless communication systems

Deep learning (DL) architectures including recurrent neural networks (RNNs) and convolutional neural networks(CNNs) are being exploited with outstanding achievements in wide-ranging fields from natural language processing and computer vision to economics and bioinformatics. Recently, DL is potentially

studied for the tasks of signal classification and modulation recognition, wherein the facilitation of automatically powerful feature learning enables greater accuracy.

CNNs capably extract more meaningful features of discrimination at multi-scale feature representations for the multi-class classification task

2.2. LITERATURE REVIEW

The basic models in Deep learning can be divided into three categories: multi-layer perceptron, deep neural network, and recursive neural network. Its representatives include DBN, convolutional neural network (CNN), recurrent neural network (RNN) and some hybrid models , respectively. In recent years, researchers use these models or improved models to recognize and classify signal modulation types.

Deep Belief Network (DBN)

Feature Deep belief network has been introduced by Hinton and his collaborators in 2006 [10]. It consists of multiple layers of restricted Boltzmann machines (RBM). RBMs are energy-based models and have the modeling capacity to represent complex distributions. DBN consists of three RBM units stacked together. Each RBM has two layers: an upper

Structure of deep belief network. hidden layer and the lower visible layer. When stacked into the network, the RBM1 hidden layer and h1 encodes features from the input layer v and hence, the data acts as the input layer of RBM2. For data that is marked in the training set, the visible layer of the last RBM contains both the hidden layer unit of the previous RBM and the labeled layer unit.

DBN is a probabilistic generation model and can produce a joint distribution between observation data and labels. It has been successful in speech recognition [26] - [28], image recognition [14] and automatic modulation recognition [23] and other fields. In [18], [19] the authors use the spectral correlation function (SCF) as preprocessed data to enter it into a DBN-based identification scheme. They transform the 3-D SCF pattern of modulation signals received in 2-D SCF patterns. Then, the grayscale images of the 2-D SCF patterns are used as input data for the semi-supervised training of the DBN. Get a greater accuracy of the classification in the presence of environmental noise. Using the scheme, authors [20] could detect and identify micro unmanned aerial systems. The authors of [21] use the amplitude information and the spectrum of the reception signal as DBNS training data. The limitation of this scheme is that the accuracy of recognition of the noisy PSK is lower, since the phase information is more accurate in the training data.

A common use of DBN is the extraction of features. Extraction of functions can be used in different concepts with different granularity. The authors of [22] suggest a combination of DBN and SVM, with the stacked RBM networks that are used to form a DBN structure to extract characteristics from the input data. SVM is used to classify features extracted.

Neuron units are unavoidable, DBN models in MR have a result of a high computational complexity compared to conventional antiquity in computational complexity. The authors of [24] use the average of SCF-of I and Q as input for the DBN-based pattern. Recognize and maintain an MR scheme based on DBN with low complexity. They represent the multiplying weight constants during the training process using -1, 0, or 1 and use approximation functions to achieve direct mapping to digital logic circuits. Such a scheme can perform identification in FPGA hardware for real-time processing.

There are also problems with over-fitting in DBN. Due to the vanishing gradient, the training effect of the lower and higher levels is different in the depth of the network. In this case, the mandatory fault monitoring training will fit the model directly to the input data, which will lead to the overfitting phenomenon. The appropriate network depth should be selected from various training data and network parameters in order to achieve better recognition results. In the scheme of [21] the DBN is with 3 hidden levels show the best result.

Convolutional Neural Network(CNN)

CNN is a feedforward neural network which contains convolutional computation and deep structure. It is a popular DL model. The first convolutional neural network is Time
Delay Neural Network (TDNN). It has two hidden layers and can discover acoustic-phonetic features as well as the temporal relationships between them. One of the advantages
of CNN is translation-invariance. It is not blurred by temporal shifts in the input. After TDNN, LeCun constructed a convolutional neural network, LeNet [22], for image classification, and LeNet-5 for recognition of handwritten numbers. LeNet-5 and its subsequent variants define the basic structure of modern convolutional neural networks.

With the improvement of deep learning theory, the use of CNN models developed quickly and completely. Various theories and optimization of learning are introduced and developed. Representative CNN algorithms include Alexnet, ZFNNet, VGGNET and Google LetNet and Resnet.

CNN has a number of merits such as local perception, weight sharing and shift invariance. It exploits spatially local correlation by enforcing a local connectivity pattern of adjacent layers, sharing weights across each layer [17].

The basic assumption of CNN is that the input data is unchanged. Sampled communication Signals given in accordance with the basic hypothesis. In recent years, deep learning techniques have reached the level of pattern identification. CNN's joint architecture is on. Wang et al. CNN is applicable to radar waveform detection by converting unique radar signals into time frequency images (TFI) using the time frequency analysis a convolutional neural network construct for frequency variation models [26]. Radio-dimensional signals are images of transform spectrograms using the STFT (Short Time Discrete Fourier) form entered into CNN [33]. Constellation diagrams are used to create CNN in [30] and [35]. In [30] the authors combine

two controversial neural networks (CNNs) that were trained on different data sets. In addition to the charts of the constellations, they also use phase and quadrature samples (IQ) and receive a better classification of the QAM signal as a result of the low signal / noise ratio. In [35] data, the authors use the accompaniment network classifier (ACCANs) as an Advanced Generator training method to suppress the center of the surface and the refractive model. It can improve the CNN classification 0. 1% -6% increase in accuracy.

Recurrent Neural Network(RNN)

Fully connected DNNS have a significant limitation: The signals of each neural layer can only be transmitted to the top layer, and sample processing is independent at each time. No changes to the screens can be modeled, and can only be used under the conditions that inputs and targets can be encoded with constant citation marks from vectors [15]. In many cases, such as natural language processing, speech recognition, handwriting recognition, and other applications, the timing of the sample occurrence is very important [26]. The output of neurons can act directly on each other in the following tag. As the sequence progresses, the previous level is about the next hidden level. The biggest difference between RNN and the basic neural network is that the latter only creates weighted connections between levels, while the former creates weighted connections between neurons at the same level. Fully connected DNN has a significant limitation. Signals from each level of neurons can be sent only to the top layer and sample processing is independent at all times. Modifications cannot be modeled in Thunderbolt sequences and can only be used when lenses can be encoded using solid dimensional vectors and other applications. The order of the occurrence of time sequence is very important. There are weights between neurons in the hidden layer. The output of the neuron can be directly act on itself on next time stamp. The order is continued, the previous level influences the next hidden layer. The biggest difference between RNN neural network and basic neural network is that the latter only adjusts the weighted connections between layers, while the first weighted connections between neurons occurs in the same layer.

Hybrid Model

A combination of CNN and LSTM Called CLDNN is proposed in [37]. Two or three convolutional layers are followed in the scheme. . It can be viewed as a hybrid model. CNNS and LSTMS are Complementary in their modeling skills, As CNNs are good at Reducing frequency fluctuations and LSTMs are good at temporal modeling.

Researchers often combine CNN with the LSTM algorithm as in [38] - [41] in order to identify modulation schemes. The hybrid model of CNN and LSTM is shown in the picture. In the hybrid model, an LSTM layer is added to the CNN architecture. The input data is imported into the CNN layer and the CNN result is fed into the LSTM layer. The CNN layer extracts the implicit Information in the dimension of time and transmits the highest quality properties and high concentration features on the LSTM layer. The authors of

[38] apply the CLDNN architecture and get the best performance between all architectures of the tested network.

2.3. PROPOSED METHODOLOGY

Deep learning increased the learning capacity of the features directly in highly dimensional unprocessed s data, the deep learning algorithms in images and extraction of certain audio features and supervised learning in general, so as a strong candidate carried out for classification task modulation ensure an integrated understanding of AMC with deeper Learning algorithms solves the central problem as the characteristics of the samples is selected and extracted. Therefore, it shows the combination of simple functions in more efficient and more complex features to achieve the classification in more efficient and complexes, moreover, deep neural networks have a multilayer structure that can better extract the signal properties by avoiding the lengthy manual selection of data properties. In this project we start with the development of a DCNN network with a limited size, testing its performance and then developed an even deeper network that is inspired by many art statistics inspired by many art statistics algorithms.

The architecture of Deep CNN is as follows:

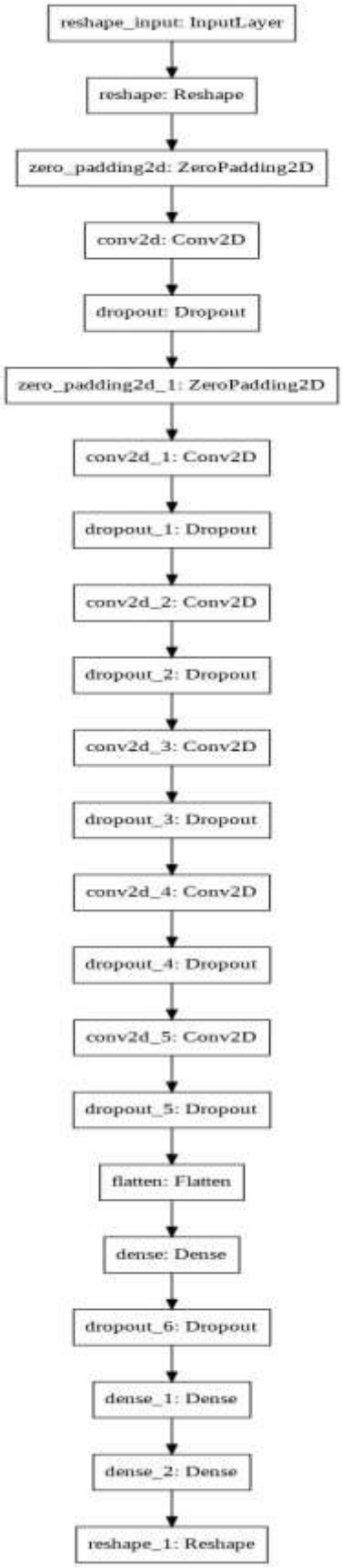


Fig3: Architecture of Deep CNN

4.1 Dataset

We use the data set RADIOML2016.10B as the basis for the evaluation of the modulation recognition task. The data used in the project were adopted by the 6th annual GNU annual conference in 2016. The dataset enables automatic learning researchers with new ideas to dive straight into an important technical area. without the need to collect or Generate new data sets and enable a direct comparison with the effectiveness of previous work. The data set is generated with GNU Radio, which consists of digital and analog modulations with different signal-to-noise ratios. The data set is divided into two parts: one large set is used to train the deep neural network and another example is used for validation. Another set is used and called the test set.

4.2 Pre-Processing

The dataset is divided into two parts:
600000 samples are used for training the deep neural network and 600000 samples for validation. All models and training are done with the Keras with TensorFlow as a deep learning library using a TITAN RTX 24G GPU. The Adam optimizer was used for all architectures, and the loss function was the categorical cross-entropy function. We also used ReLU activation functions for all layers, except the last dense layer where we used SoftMax activation functions. We used a minimum batch size of 1024 and a learning rate of 0.001.

4.3 Training the Model

Our DCNN model contains 1 input layer, 6 conv2D layers, 2 Dense layers and 1 output layer with a few dropout layers in between.

(a). On training and Validation dataset the DCNN model is trained.

(b). After training, true-positive, false-positive, true- negative, false-negative of the test set were recorded successively.

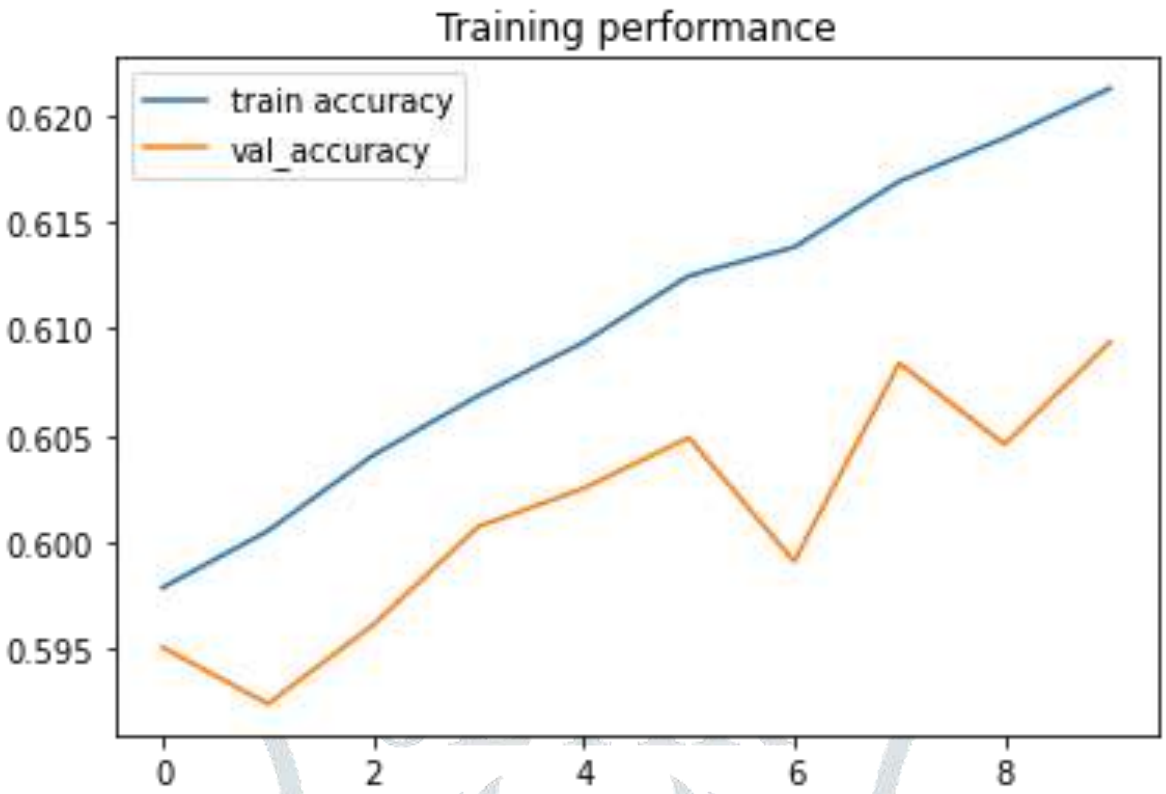


Fig4. Training vs Validation accuracy of DCNN Model.

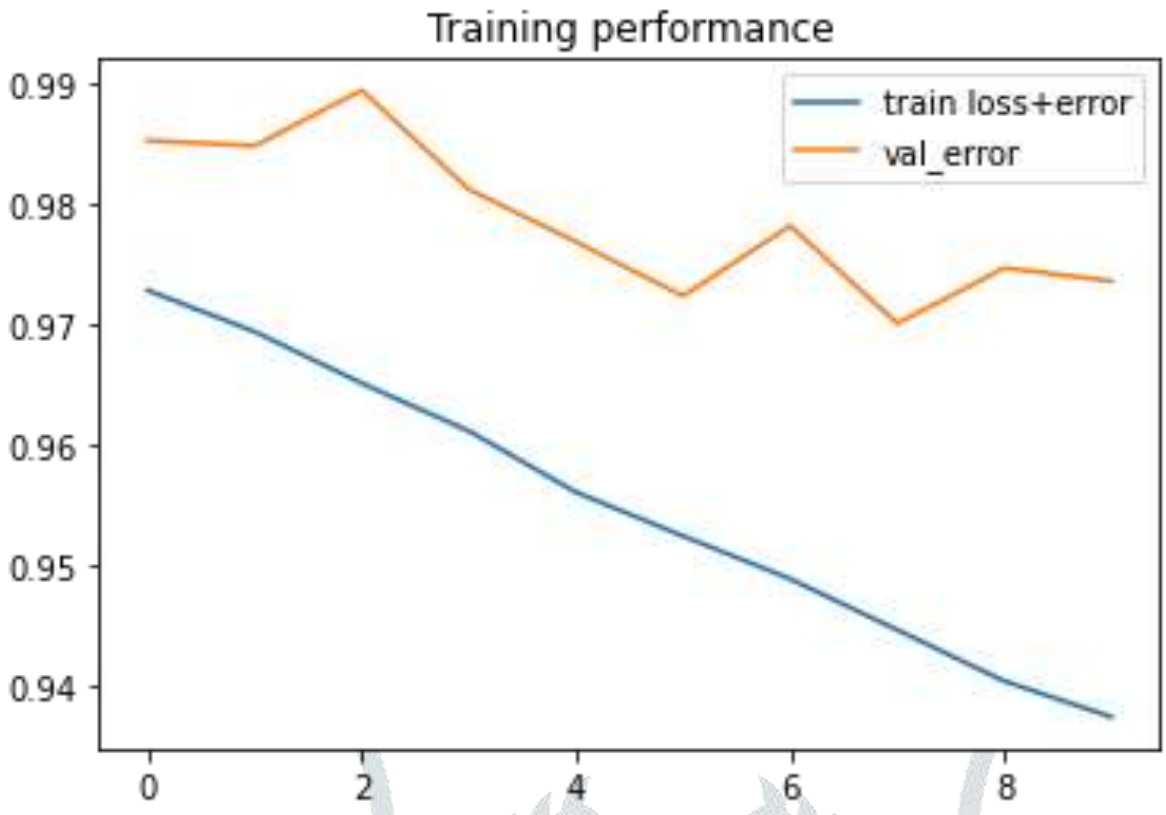


Fig5: Training loss vs Validation loss of DCNN Model.

CHAPTER 3

DEEP CNN MODEL

Since the 2012 ImageNet won the war-trying with Krizhevsky et al, their "Alex net" network has been successfully applied to a larger variety of mission vision computers, for example to counter-detection, segmentation, People set estimates, video classification, tracking objects, and the super-successful spurred a new line of research focused on higher detection of conventional neural networks. Beginning in 2014, The quality of the architecture network is significantly improved by using deeper and wider than the network. VGG Net and Google Net yielded are similar to that of high performance in the 2014 ILSVRC classification challenge. An interesting observation is that profit in performance classification tends to significantly transfer quality in a variety of domain name applications. This means that improved architecture in the Convolutional Architecture can be used to improve performance for most other computers that view the task

is the day. reliant on high quality, learned the image of the features. Also, improvements in the Quality Network led to new domain name application for network convolutional where Alex Net features may not compete with hand design, made solutions, They Suggested generation in detection.

although VGGNet attractive features of simple architecture, this comes at a high cost: evaluation of networks requires a lot of calculations. On the other hand, the establishment of Google Net's architecture is also designed to perform well even under strict memory and budget calculations. For example, Google Net hired only 5 million parameters, which represented the 12th, reduced with respect to its predecessor, Alex Net, which used. Additional 60 million parameters-more, VGGNet uses about 3x parameters, rather than the calculation of the inception, also lower than VGGNetor higher operational success. This makes it possible to use a network of funds in large data situations, where huge amounts of data are required. It has been processed at reasonable prices or situations where memory or calculated capacity is limited, for example, in vision settings. It is possible to alleviate these parts by using specific solutions to tar-get memory use or by optimization of certain operations through technical calculations. However, these methods add extra complexity. To optimize the building of architecture, as well as expand the performance gap. Again still, the complexity of the architecture inception makes

It is difficult to make changes to the network if the architecture is adjusted naively, A large piece of computational profit can be lost immediately. That caused various design decisions of google net's architecture. This makes it much more difficult to adapt to it for new use-in case of maintaining its effectiveness. For example, if it is considered necessary to increase the capacity of some When into a stylish model, Conversion simplicity of just double the number of all size bank filters will lead to a 4x increase in both cost and quantity calculations. parameters. This can prove prohibitive or unreasonable in many of the facts of the script, especially if the benefits combination is modest. In this article, we start with the description of some general principles and optimize that idea that proves to be useful for extending the scale to the network effectively. Although our principle is unlimited to become network type, they are easier to observe in which the context is the same structure of the establishment of building block style is flexible enough to combine natural restrictions. This is activated by generously using the reduction and parallel structure of the module when the module is established, which allows to mitigate the effects of near-changing structures. That composition. Still, a need to be cautious about doing so, as some guidelines should be observed to maintain the high quality of the models.

6.1. General Design Principles

We have design principles based on large-scale experimentation with various architectural choices with convolutional neural networks(CNN).At this point, the utility of the principles below is speculative and additional future experimental evidence will be necessary to assess their accuracy and domain of validity. Still, grave deviations from these principles tended to result in deterioration in the quality of the networks and fixing situations where those deviations were detected resulted in improved architectures in general.

1. Avoid the representational bottlenecks, mainly early in the network .Feed-forward networks are also represented by an acyclic graph from the input layers to the classifier or regressor. This shows a clear direction for the information flow. For any cut separating the inputs from the outputs, we can access the amount of information passing though the cut. One should avoid bottlenecks with extreme compression .In general, the representation size should gently decrease from the in- puts to the outputs before reaching the final representation used for the task at hand. Theoretically, an information content cannot be assessed merely by the dimensionality of representation as it discards the important factors like correlation structure; the dimensionality merely provides a rough estimate of information of the content.

2. Higher dimensional representation is easy to process within the network, adding activations to the tiles in a convolutional network helps. provides more messy features, network causing trains.

3. Spatial aggregation can be done more than a lower dimension embedding without much loss or loss in any representative Energy, for example. Before further study spread out Constitution, one can re-duce the dimension of the input value display before the area aggregation by do not expect serious advertising results, we assume that the reason for a strong relationship between adjacent unit results. Very little data loss during the new dimension, duction if the output is used in the total context. The area states that these signals should be easily compressed, dimensional reductions even promote faster learning.

4. Balance the width and depth of the network. Best performance an be achieved by balancing the number of filters per stage and depth of networks. Increasing both the width and depth of the network can contribute higher than the quality of the net-operation. However, improved optimization for a continuous number of calculations can be achieved if both are increased in parallel. Budget calculations should therefore be distributed in a balance between the depth and width of the principles that can make the feeling, it is not simple to use them to improve the quality of the net-working out of the box. The idea is to use them wisely in unclear situations only.

CHAPTER 5

RESULT

5.1 ENVIRONMENT

Our task was to train a deep convolutional neural network (DCNN) that could identify and classify digital signals. We used RML2016.10b.dat from which we have selected 10 categories [8PSK, AMDBSK, BPSK, CPFSK, GFSK, PAM4, QAM16, QAM64, QPSK, WBFM], a dataset containing signals in the form of arrays from these 10 categories. Signals from each category came in 20 different SNRs (Signal to Noise Ratio) ranging from -20 to 18.

DL methods continue to show enormous promise in improving radio signal identification sensitivity and accuracy, especially for short-time observations However, DCNN can automatically extract features so that it can save a lot of time and labor. After evaluation of model on test dataset the results are recorded. Accuracy of each signal is as follows:

8PSK(65%),AMDBSK(81%),BPSK(65%),CPFSK(66%),GFSK(71%),PAM4(72%),QAM16(44%),QAM64(57%),QPSK(59%),WBFM(25%). The overall accuracy of model is 60.84%. The figure represents the confusion matrix of the model and accuracy of each signal is specified as shown:

Fig6. Confusion Matrix of DCNN Model

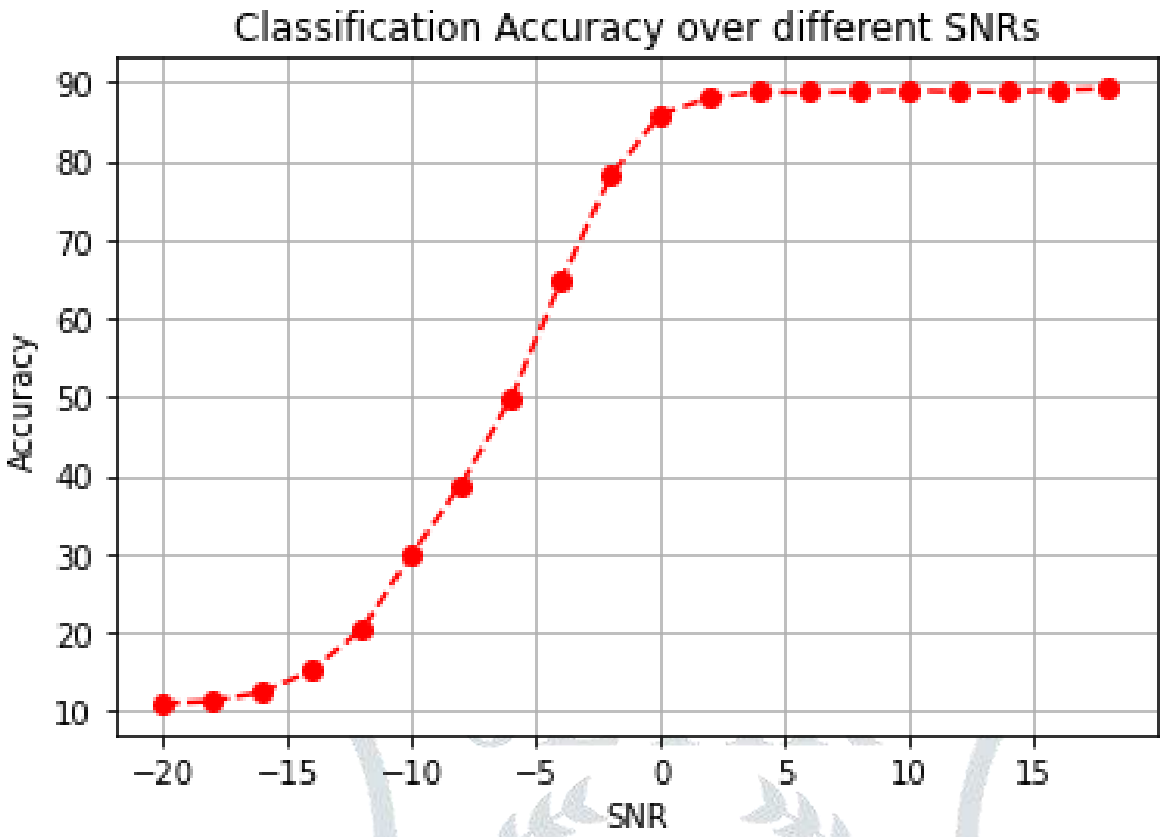


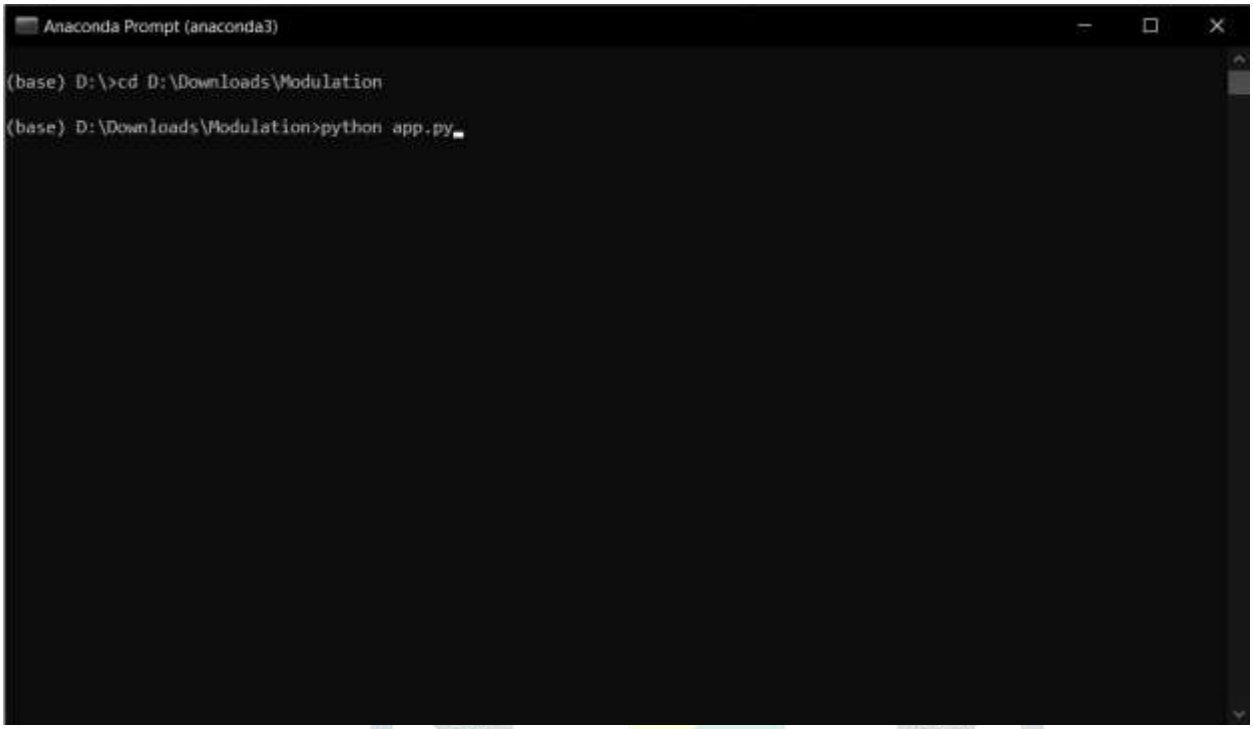
Fig6: Classification Accuracy over different SNRs.

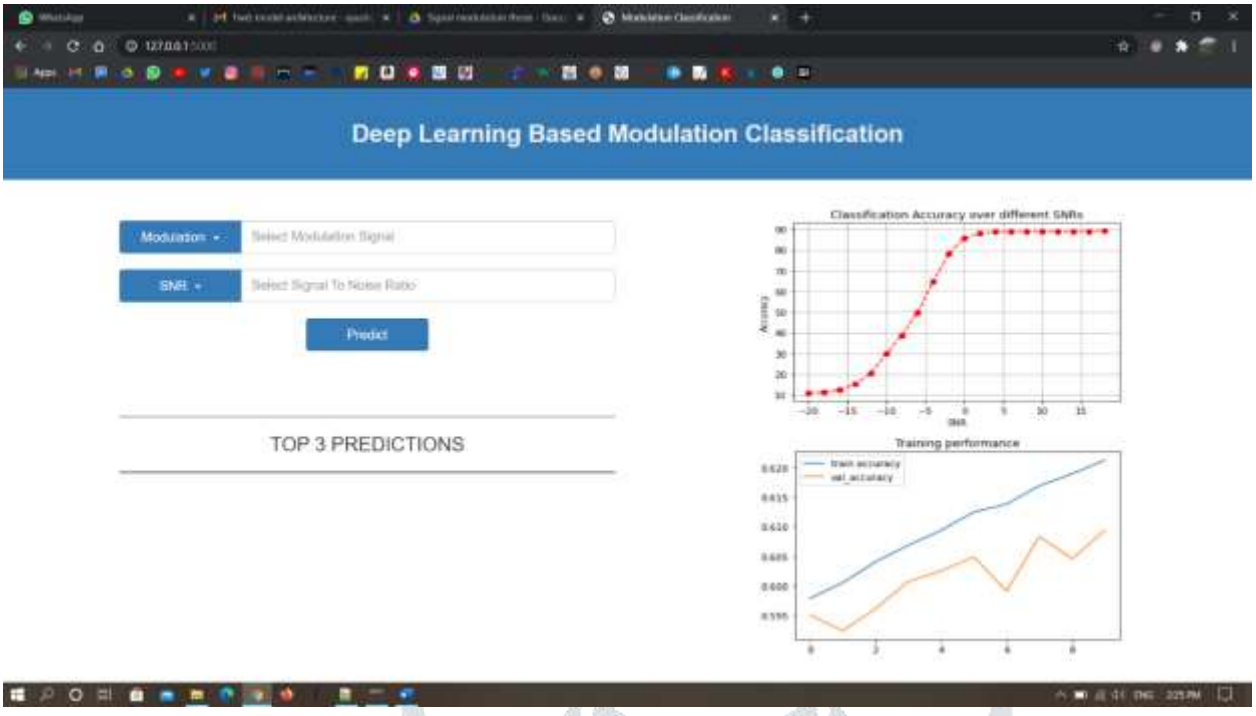
As the SNR ratio increases, classification accuracy of the DCNN model also increase.

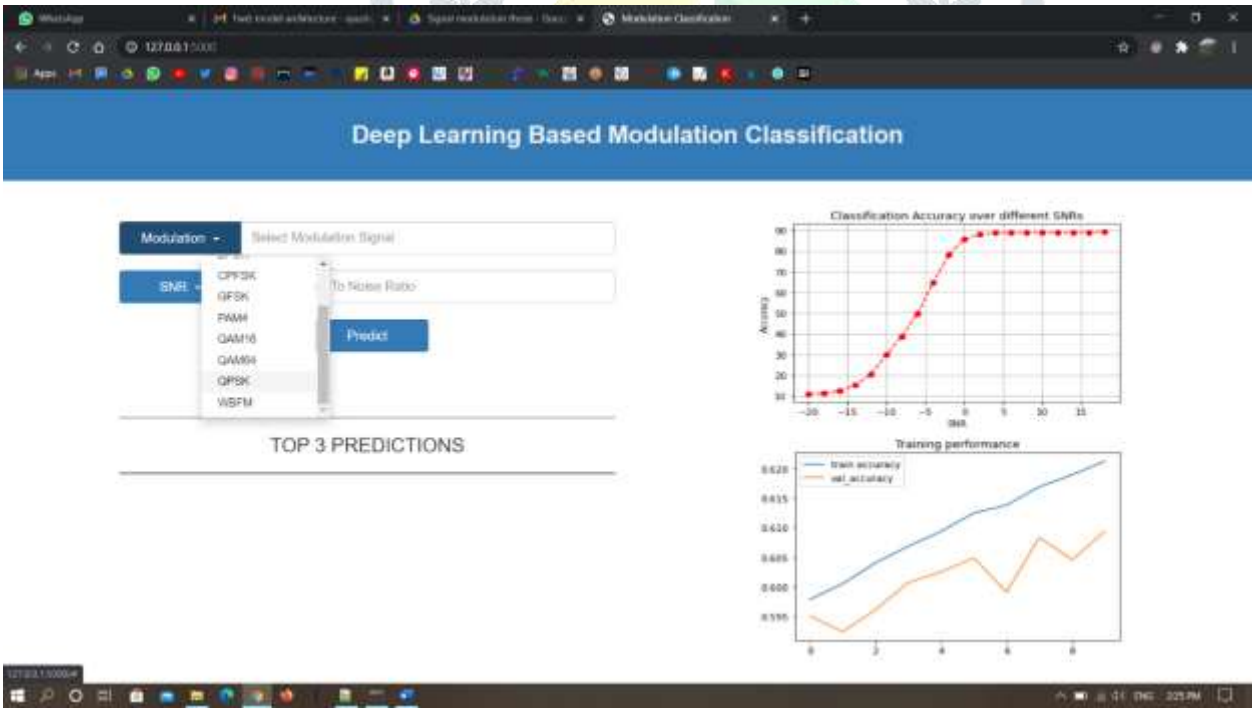
In those signals where noise is minimum, the accuracy of model is around 90%. On the other hand, in those signals where the noise is maximum the accuracy of model is below 50%

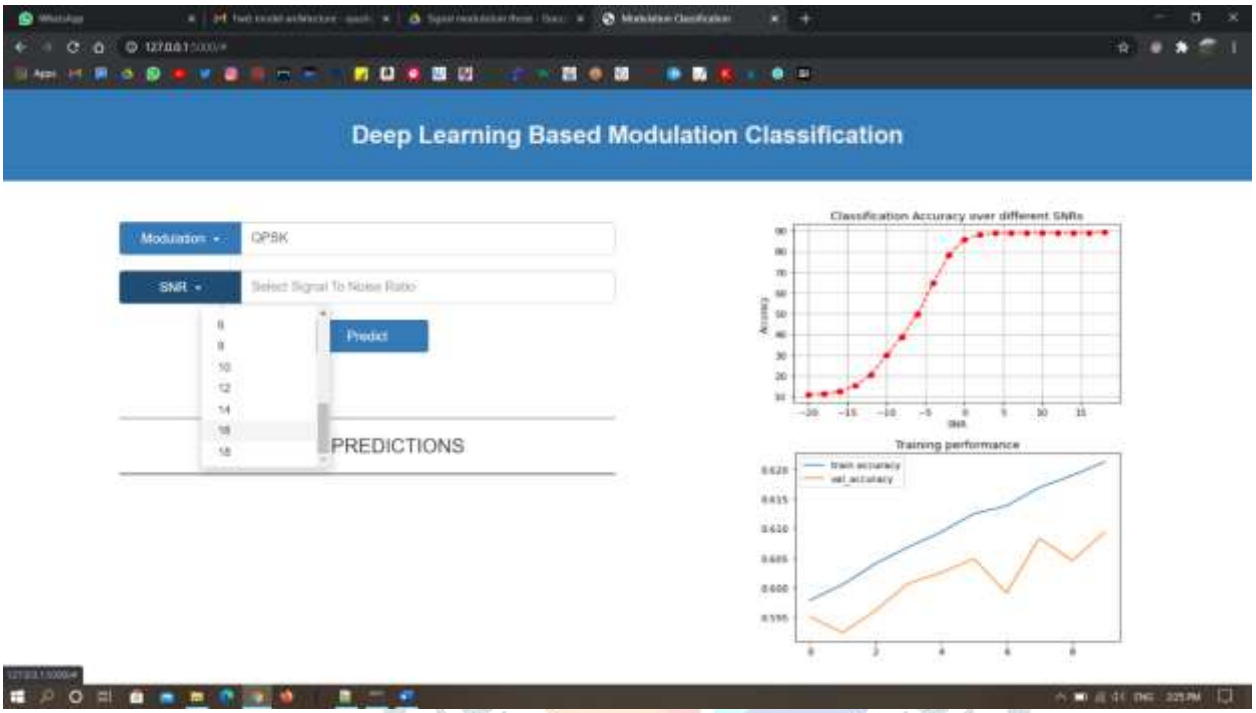
5.2. SCREENSHOTS OF RESULTS

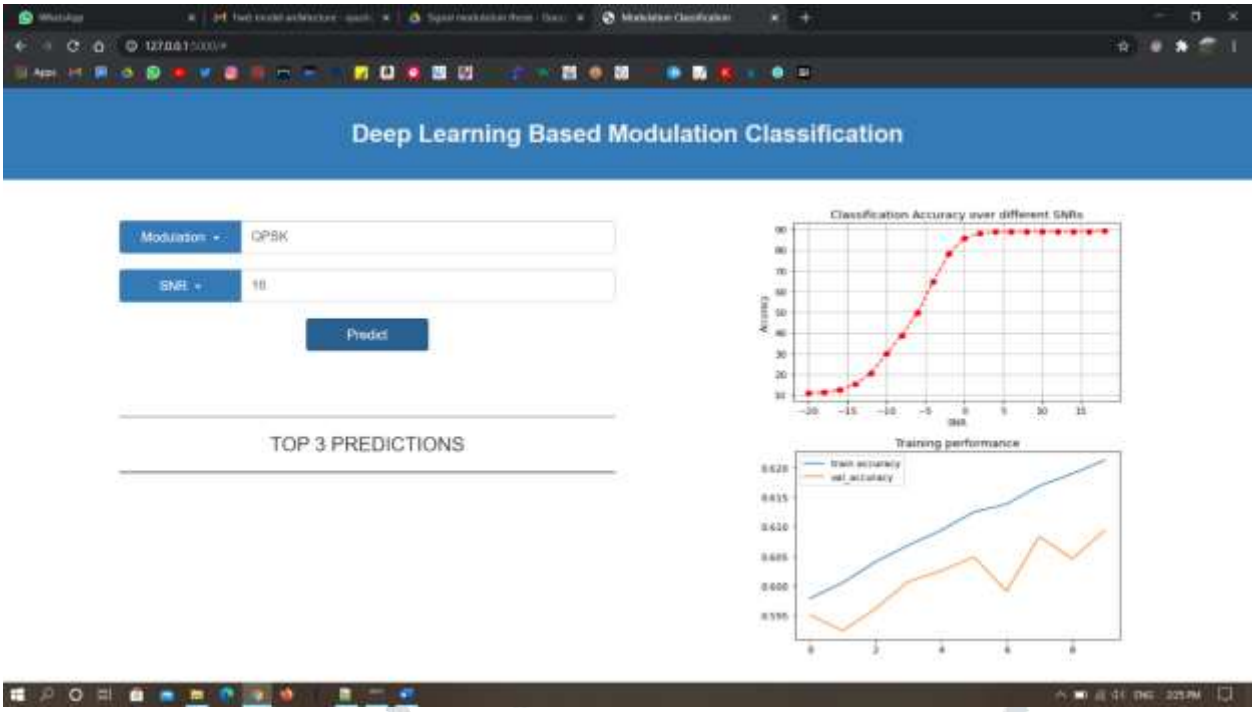
After implementing the Deep learning-based modulation classification system, the efficiency of the system is evaluated as follows:

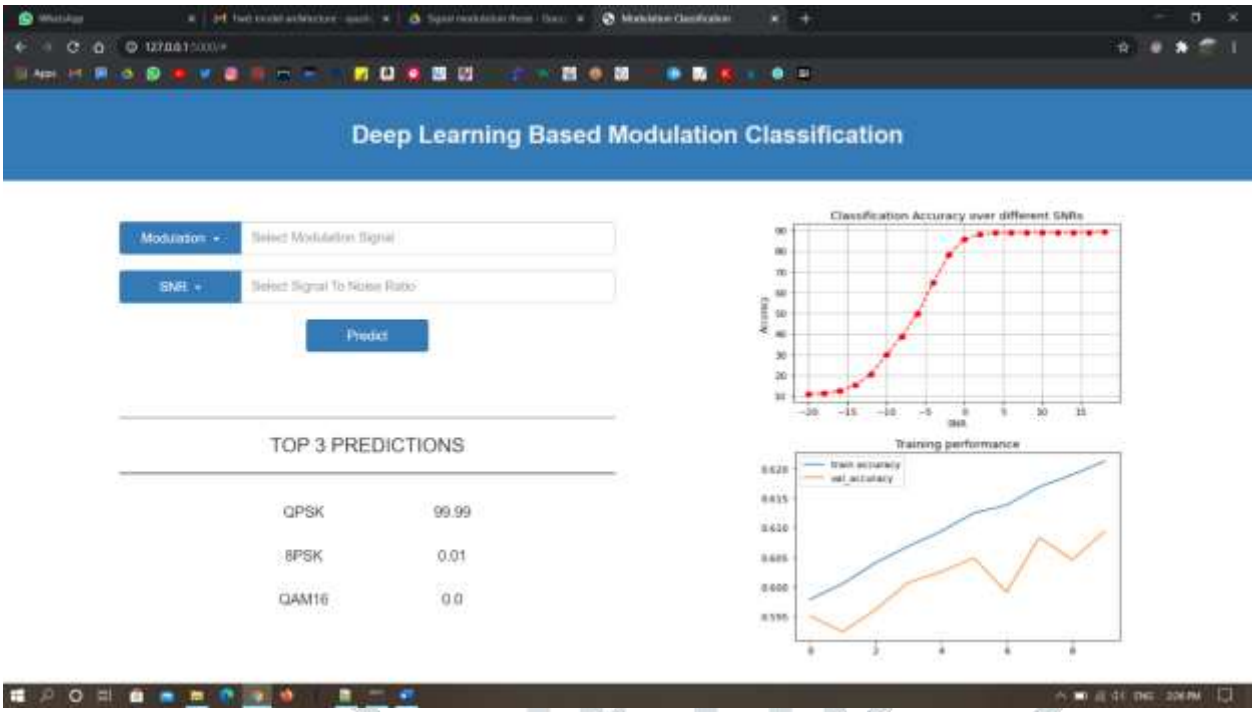



Deep Learning Based Modulation Classification
Modulation
Select Modulation Signal
SNR
Select Signal To Noise Ratio
Predict
TOP 3 PREDICTIONS
Classification Accuracy over different SNRs
Accuracy
SNR
Training performance
train accuracy
val_accuracy


Deep Learning Based Modulation Classification
Modulation
Select Modulation Signal
SNR
To Noise Ratio
CPFSK
GFSK
PAM4
QAM16
QAM64
QPSK
WBFM
Predict
TOP 3 PREDICTIONS
Classification Accuracy over different SNRs
Accuracy
SNR
Training performance
train accuracy
val_accuracy


Deep Learning Based Modulation Classification
Modulation
QPSK
SNR
Select Signal To Noise Ratio
Predict
PREDICTIONS
Classification Accuracy over different SNRs
Training performance


Deep Learning Based Modulation Classification
Modulation
QPSK
SNR
10
Predict
TOP 3 PREDICTIONS
Classification Accuracy over different SNRs
Accuracy
SNR
Training performance
train_accuracy
val_accuracy


Deep Learning Based Modulation Classification
Modulation
Select Modulation Signal
SNR
Select Signal To Noise Ratio
Predict
TOP 3 PREDICTIONS
QPSK 99.99
8PSK 0.01
QAM16 0.0
Classification Accuracy over different SNRs
Accuracy
SNR
Training performance
train_accuracy
val_accuracy

5.3. SUMMARY

With the development of AI, DL has been applied to automatic modulation classification and has achieved very good results. In this thesis, we introduced a deep convolutional neural network for implementing radio modulation signal identification task.

The proposed DCNN model have excellent performance for modulation classification in the thesis. The experiment shows that the classification accuracy of the proposed model is highest with the varying SNR among the signals are:

8PSK (65%), AMDBSK (81%), BPSK (65%), CPFSK (66%), GFSK (71%), PAM4 (72%), QAM16 (44%), QAM64 (57%), QPSK (59%), WBFM (25%).

This provides a new idea for modulation classification aiming at distraction time signals.

CHAPTER 6
CONCLUSION AND FUTURE SCOPE

6.1. CONCLUSION

In this work we have extended prior work on using deep

convolutional neural networks for radio signal classification by heavily training deep convolutional neural network for the same task. We have also conducted a much more thorough set of performance evaluations on how this type of classifier performs over a wide range of design parameters, channel impairment conditions, and training dataset parameters.

6.2. FUTURE SCOPE

This network approach achieves state of the art modulation classification performance on a difficult new signal database both synthetically. Other architectures still hold significant potential, radio transformer networks, recurrent units, and other approaches all still need to be adapted to the domain, tuned and quantitatively benchmarked against the same dataset in the future.

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