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AI BASED RADAR WAVEFORM CLASSIFICATION SYSTEM

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Abstract - *Data flowing from radar and electronic warfare (EW) systems to the analyst's screen will determine the course of action in any given mission. Bearing in mind that decisions need to be made, at times in seconds, it's critical for radar and EW systems to quickly sift through that data and turn it into actionable intelligence. To achieve this goal, the industry is using artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques to program these systems and make them into smarter, more autonomous tools. The main objective of this project is to overcome the certain shortcomings in the present radar system i.e. they take a lot of time to detect the signals, accuracy is compromised in most cases and signal is highly prone to external interference. This project involves a combination of various fields to build a model that can be applied effectively for different radar applications. The radar signal learning is vital for reduction of clutter and noise. The dynamic processing is very important for artificial systems. The model was trained on 2.1 million signals of twenty-four different classes with varying SNR values in the range of -18 to 30. The model shows a promising accuracy of 96% for appreciable values of SNRs.*

***Key Words*: Artificial Intelligence, Machine Learning, Deep Learning, Signal Classification, Neural Networks, Radar Applications**

1. INTRODUCTION

Radar is a detection system that uses radio waves to determine the range, angle, or velocity of objects. It can be used to detect aircraft, ships, spacecraft, guided missiles, motor vehicles, weather formations, and terrain. A radar system consists of a transmitter producing electromagnetic waves in the radio or microwaves domain, a transmitting antenna, a receiving antenna (often the same antenna is used for transmitting and receiving) and a receiver and processor to determine the properties of the object(s).

Radar was developed secretly for military use by several nations in the period before and during World War II. A key development was the cavity magnetron in the United Kingdom, which allowed the creation of relatively small systems with sub-meter resolution.

The advantage of AI in the field of signal classification is that the algorithms can adapt to changing environments and scenarios. AI can also replace human operators in systems where human involvement is required for target recognition. Automatic learning of radar waveforms, feature extraction, identification is required to use in artificial intelligence Systems.

The radar architecture has to be improved to handle more targets dynamically with an Artificial intelligence processing. The radar signal learning is vital for reduction of clutter and noise. The automatic radar target detection and dynamic processing is very important for artificial systems. To design an intelligent radar system, we use current technologies like Neural Networks, Machine learning, deep learning and Bayes tracking concepts

1.1 MOTIVATION

Artificial neural networks (ANN) or connectionist systems are computing systems that are inspired by, but not identical to, biological neural networks that constitute animal brains. They use the processing of the brain as a basis to develop algorithms that can be used to model complex patterns and prediction problems. This has motivated us to work on developing an artificial intelligence radar system which will imitate the action of a human brain to predict and classify the waveforms by consuming less time with higher accuracy, and also apply the fundamentals of signal processing and also utilize the knowledge on neural networks to achieve classification of signals accurately.

1.2 AIM AND OBJECTIVES

The main aim of the proposed work is to develop an automated model which has capability of identifying the class of the radar waveform where signal is given as a test data from the dataset at a particular SNR value.

The main objectives are to develop an automated model by making use of train and test signal data of various radar waveforms in order to identify/ classify the waveform to particular class.

1.3 PROPOSED SYSTEM

This study developed a platform that uses deep learning for signal processing to identify the radar waveform class from signal data uploaded by an end-user. The proposed system could detect and differentiate uploaded signal data for very low values of SNRs also. With an overall accuracy is high for the training dataset using Residual Neural Network model. This study ultimately aimed to design an automatic system for differentiating among various radar waveform classes with shared fundamental characteristics but minor variations in appearance. The system methodology is described in Fig 1.

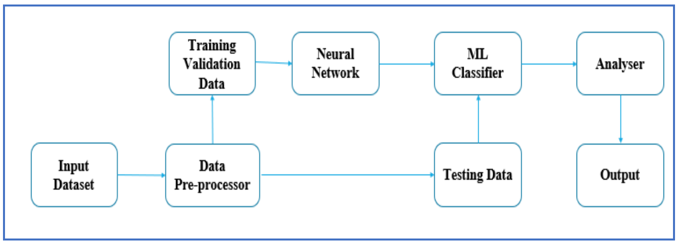

Fig -1: Proposed System

2. LITERATURE SURVEY

The earlier approaches for the baseline signal classification was based on digital modulation techniques, higher order statistics and cyclo-stationary moments [1][2] are among the most widely used features to sense and detect signals with strong periodic components such as are created by the structure of the carrier, symbol timing, and symbol structure for certain modulations . When modelling a wireless channel there are many compact stochastic models for propagation effects which can be used [3]. Deep Learning Classification Approach relies today on SGD to optimize large parametric neural network models. Since Alexnet [4] and the techniques, there have been numerous architectural advances within computer vision leading to significant performance improvements.

In Automatic radar waveform recognition based on time-frequency analysis and convolutional neural network [5] transformation of one-dimensional radar signals into time-frequency images (TFIs) using time-frequency analysis and convolutional neural network is designed to recognize the frequency variation patterns exhibited in TFIs. In Waveforms classification based on convolutional neural networks [6] Firstly, convolution and pooling operations are cross used for generating deep features, and then fully connected to the output layer for classification. Different from other traditional approaches which need human-designed features, CNN can discover and extract the suitable internal structure of the input waveform to obtain deep features for classification automatically.

3. METHEDOLOGY

The methodology acquired to build this model is as follows

3.1 DATASET ACQUISITION

The dataset contains several variants of common signal types used in satellite communication. The dataset includes both real signals and synthetic signal data with added noise to model real conditions. The dataset consists of 2-million labelled signal examples of 24 different classes of signals with varying SNRs

3.2 PREPARING THE DATASET

The collected images were divided into train and test datasets i.e. 80 percent of the signal waveforms were used as training data 10 percent as validation data and the remaining 10 percent for the purpose of testing the trained model. The dataset is described by table 1 as follows:

Table -1: Dataset Description

DATASET OF WAVEFORMS WITH THE NUMBER COUNT		
CLASS NAME	NUMBER OF SIGNALS	SNR VALUE RANGE
16APSK	87677	-18 to 30
32PSK	86992	-16 to 30
32QAM	86822	-18 to 28
FM	86868	-14 to 30
GMSK	86936	-14 to 26
32APSK	87005	-18 to 30
OQPSK	87902	-18 to 28
8ASK	87921	-18 to 30
BPSK	87323	-14 to 26
8PSK	87917	-18 to 28
AM SSB SC	87218	-16 to 30
4ASK	87549	-16 to 30
16PSK	87178	-18 to 30
64APSK	87532	-18 to 28
128QAM	87731	-18 to 30
128APSK	87840	-14 to 26
AM DSB SC	87660	-18 to 28
AM SSB WC	86961	-18 to 30
64QAM	86769	-14 to 26
QPSK	87432	-14 to 26
256QAM	86982	-18 to 28
AM DSB WC	87430	-14 to 26
OOK	87853	-18 to 30
16QAM	87453	-18 to 30
Total	2096951	-18 to 30

3.3 DATASET PREPROCESSING

Each signal example in the dataset comes in I/Q data format. The Original dataset which is saved in hdf5 form is converted to numpy form as processing with numpy form has its own advantages such as it occupies less space, faster to process and ease of access is high. The various classes of waveforms are as shown in fig 2.

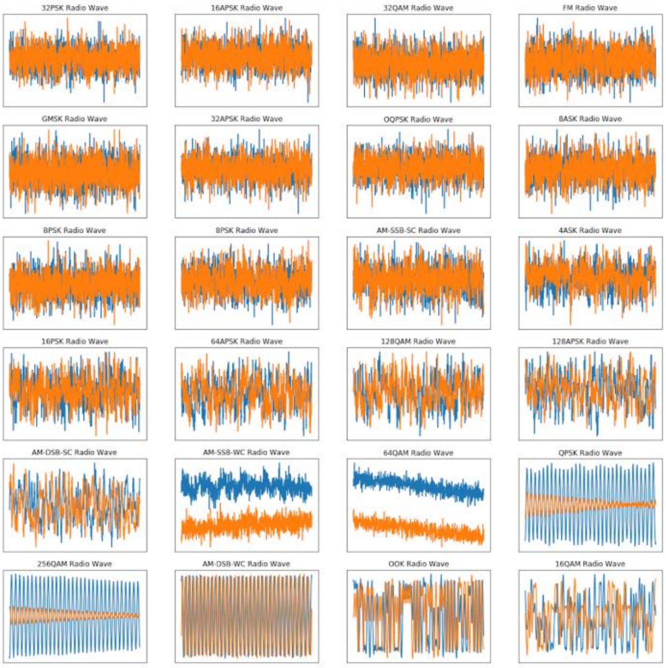

Fig -2: Classes of Waveforms

3.4 NEURAL NETWORK ARCHITECTURE

In Neural Networks Training happens over several epochs on the training data. In each epoch the network predicts the labels in a feed forward manner. The error (or sometimes called loss) is transmitted through the network in reverse, layer by layer. This is what is referred to as back propagation. As the error is received by each layer, that layer figures out how to mathematically adjust its weights and biases in order to perform better on future data. As the loss progresses backwards through the network, it can become smaller and smaller, slowing the learning process. This is called the vanishing gradient problem which gets worse as we add more layers to a neural network.

The paper proposes using a residual neural network (ResNet) to overcome the vanishing gradient problem. It accomplishes this by a simple architectural enhancement called a skip-connection. An example of the skip connection is shown below in fig 3:

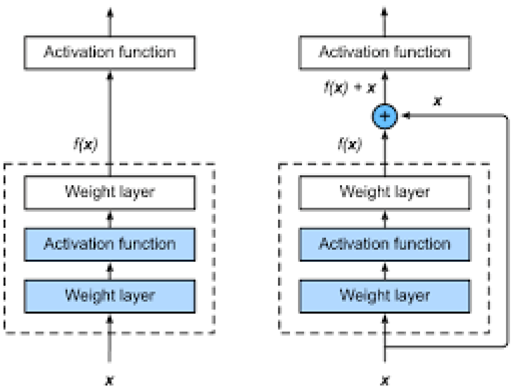

Fig -3: Skip Connection

The skip-connection effectively acts as a conduit for earlier features to operate at multiple scales and depths throughout the neural network, circumventing the vanishing gradient problem and allowing for the training of much deeper networks than previously possible. The architecture of the neural network used in this paper is described in table 2.

Table -2: Neural Network Architecture

LAYER	OUTPUT DIMENSIONS
INPUT	2 X 1024
RESNET STACK	32 X 512
RESNET STACK	32 X 256
RESNET STACK	32 X 128
RESNET STACK	32 X 64
RESNET STACK	32 X 32
RESNET STACK	32 X 16
SELU/FC	128
SELU/FC	128
SOFTMAX/FC	24

The architecture contains many convolutional layers (embedded in the resnet stack module). Convolutional layers are important for image recognition and, as it turns out, are also useful for signal classification.

The ResNet was developed for 2D images in image recognition. In this architecture, 1D layers and convolutions are used, but the skip connection is generic for any kind of neural network.

3.5 TRAINING OF THE MODEL

The various parameters associated with the training of the Neural Network is described in table 3 as follows

Table -3: Training Parameters

PARAMETER	VALUE/DESCRIPTION
LAYERS	121
TRAINABLE PARAMETERS	2,87,466
INPUT SHAPE	2 X 1024
OUTPUT SHAPE	24
TRAINABLE CLASSES	24
GPU USED	TESLA P100
DATASET SIZE	24 GB
NUMBER OF WAVEFORMS	2,09,651
MEMORY REQUIRED	50 GB
RAM REQUIRED	16 GB
NUMBER OF EPOCHS	100
TIME REQUIRED	19 HOURS

4. RESULTS:

The Confusion Matrix for the classification model is as shown below in Fig 4.

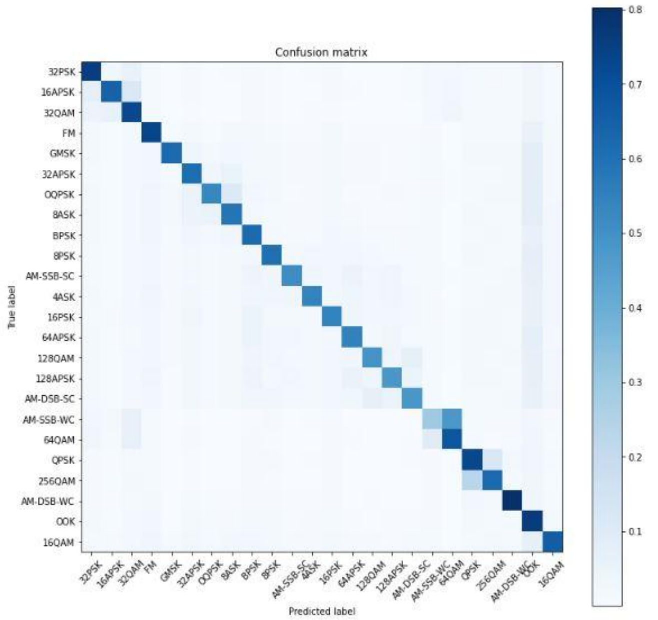

Fig -4: Confusion Matrix

The develop model was successfully tested using the test datasets and the accuracy of the model built was found to be 96.75% overall which was calculated using the following equation.

$$\textbf{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP is True Positive, TN is True Negative, FP is False Positive and FN is False Negative.

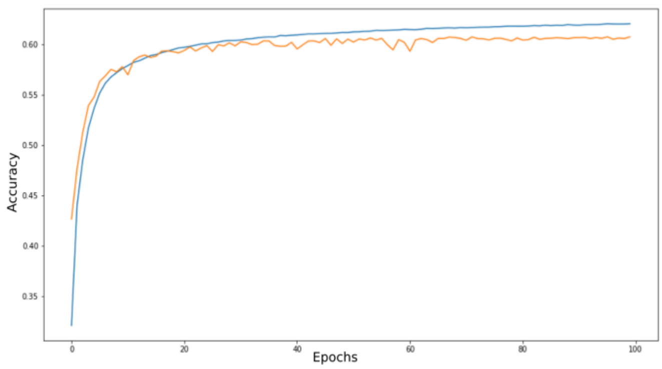

Fig -5: Model Accuracy by Epoch

The graph in Fig 5 shows a maximum classification accuracy of 60% — this is because the model is being tested to its absolute limits on a mix of clean signals and signals with very high interference. Some of the signals have so much noise that they are virtually unrecognizable. The following Table 4 and graph in Fig 6 will describe the model accuracy for different values of SNRs.

Table -3: Accuracy at different SNR values

SNR VALUE	ACCURACY In %	SNR VALUE	ACCURACY in %
-18 dB	4.26	6 dB	87.23
-16 dB	4.14	8 dB	92.87
-14 dB	4.98	10 dB	95.27
-12 dB	8.21	12 dB	96.04
-10 dB	11.52	14 dB	96.11
-8 dB	17.51	16 dB	96.49
-6 dB	22.43	18 dB	96.25
-4 dB	31.34	20 dB	96.26
-2 dB	40.65	22 dB	96.25
0 dB	52.99	24 dB	96.03
2 dB	61.46	26 dB	96.32
4 dB	73.87	28 dB	96.41

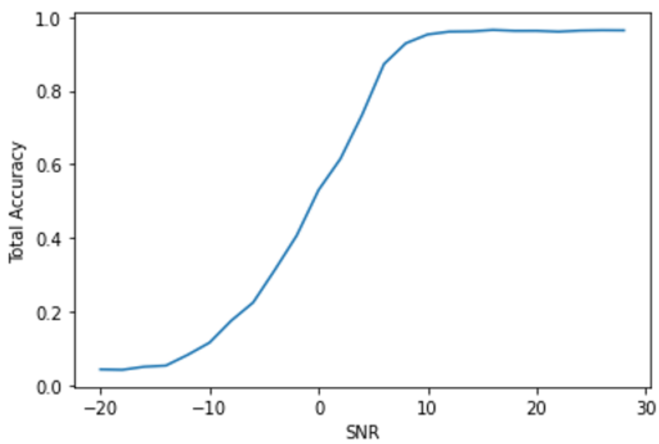

Fig -6: Accuracy by SNR

5. CONCLUSIONS

The driving force for me to choose this project is that it involves a combination of various fields to build a model that can be applied effectively for different signal classification applications Radar Applications Biomedical Applications Seismology Applications, and many more. We have used the concept of Neural Networks, as it is one of the most widely tools used which is proven to give a higher efficiency and accuracy. We are working on reducing the detection time to less than a minute. Our classification system will analyze the waveform for a higher number of cycles and will tend to give a more accurate output. Thereby reducing the interference of the other signals.

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