A Robust Computational Framework of Deep Learning for Wireless Signal Predictive Classifier

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Abstract:- In this scientific manuscript, a robust framework of deep learning predictive modeling is introduced. The prime aim of this computational system is to determine and predict wireless spectrum data set with lower computational cost. The cost-effective design of the formulated system applies training of convolutional neural network (CNN) to strengthen the prediction accuracy. The computational modeling and design optimization is carried out considering ANN stacks along with its corresponding feature neuron sets. It also implies non-recursive and less iterative design solution which makes it more scalable and robust and also determines better classification accuracy as compared to conventional approaches. The model validation is carried out with respect to a set of performance matrices such as Mean Absolute Error (MAE), Mean Relative Error (MRE), Correlation Density Function (CDF) and Root Mean Square Error (RMSE) in a numerical computing environment.

Keywords:- *Deep Learning , Predictive Modeiling ,Wireless Signals , Preprocessing , Classification.*

I. INTRODUCTION

The specialized developments, innovations and advancements in the field of Wireless Networks like Mobile Ad-hoc Network, Wireless LAN, Wireless Sensor Network and most recent pattern of Internet of things alongside propelling Wireless Communication Standards like 5G is making a chance to work together with heterogeneous remote gadgets and explore the spectrum range efficiencies which are un-used [1]. There is immense decent variety in the wireless spectrum range with setting of over and under-use of these spectrum ranges, particularly the use of unlicensed accessible spectrum bands. This un-balance circumstance of resource like spectrum range forces an extremely high level of expense and quality limitations of interferences because of cross technology condition [2]. The applications means to use fifth era radio innovation for example 5G, their prosperity is generally reliant on the balanced usage of spectrum range computational resources. The issue of proficient checking and examination of the spectrum range handling is a very crucial assignment in light of the fact that the arrangement of wireless communication paradigm is extremely complex and exceedingly dispersed [3].

The persistent information created with system generated wireless traffic ends up voluminous over timeframe and gradually become complex in the structure. The complex data features and perplexing qualities of the spectrum range information require another design methodology to be created to examine it. The persistent information created with system generated wireless traffic ends up voluminous over timeframe and gradually become complex in the structure. The complex data features and perplexing qualities of the spectrum range information require another design methodology to be created to examine it. The technique should be proficient and adaptable for ID or grouping with exact predictive capacity in a wireless networking system. The model of prediction may incorporate different arrangement properties like innovation utilized, sort of modulation types, obstruction, and so on to give huge contributions to very heterogeneous wireless networking systems to guarantee adjusted and cost-effective use of spectrum range assets [4].

In this study a robust structured system is architected where taking a wireless networking system information likeness to crude information of changed spectrum range band comprising of countless data samples to mimic a complex wireless signal attributes for a total learning procedure of AI approach of machine intelligence is utilized for different amplitudes crosswise over time space is structured. The precision of the model is approved with various error types.
In section II we give an overview of related work which identifies all the major research work being done in this area. Proposed system is discussed in Section III followed by research methodology in Section IV. Section V discusses about performance analysis and finally in section VI we make some concluding remarks.

II. RELATED WORK

The different research studies has been given extensive effort to improve the spectrum range effectiveness and tended to difficulties towards characterizing spectrum range efficiency by considering execution measurements like area spectral effectiveness and average factors of spectral proficiency [2]. So as to offer significant data about spectrum range usage, the idea of spectrum range inhabitance estimations came into the image which evaluate the time portion where certain recurrence of frequency bands are involved in the given area [3].

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The spectrum range occupancy estimations gives significant data to the clients just as improve the range database exactness which can be additionally used for spectrum range database management execution and give spectrum range sharing over operational condition [4]. The diverse spectrum range inhabitance accessible in various existing literatures for instance example [5]-[6], has been performed with single node at static area, centering time and frequency measurements. Be that as it may, this manuscript does not gave adequate data about current utilization of range information to get positive end. In [7], Marko et.al has concentrated on spectrum range inhabitance estimations on multi-measurements, for example, spatial, transient and frequency factors.

The novel study of Ding et.al [8] has investigated new approach of big data using cognitive wireless networking. The core idea behind this is rapid development of cellular networks, wireless IoT applications are greatly hampered with limited spectrum resources. To improvise spectrum utilization accuracy, cognitive radio networking paradigm is effective solution [9], which provide efficient radio environment for dynamic spectrum sharing between heterogeneous networks [10]. Additionally, cognitive radio is to use the underutilized spectrum resources by reutilizing the un-used spectrum bands in an opportunistic approach [11].

At present there are various research work being carried out in order to identify and classify wireless device spectrum data using different algorithmic and modeling approaches. Akyildiz et.al [12] presents the detailed review of the spectrum management in cognitive radio (CR) networks. The authors discussed about various research issues along with main challenges in spectrum management in CR networks. The CR Network architecture includes primary networks with band I and band II, cognitive radio network without and with infrastructure includes primary network access, CR User, CR Network access, CR Adhoc access along with CR base station. The spectrum management frame work is explained in detail with different layers architectures. The main challenges in spectrum management include spectrum decision, spectrum sharing, and spectrum mobility and protection strategies are discussed.

Conventional radio modulation recognition network is addressed in Timothy et.al [13], which includes an approach in the Conventional radio using Convolution Neural Network (CNN) and Deep NN (DNN) for modulation recognition with feature learning, evaluation of dataset with visualization, modulation effects are incorporated along with learning invariance, network evaluation, and training features. The performance of CNN and DNN with different SNR are analyzed.

Selim et.al [14] presents the spectrum monitoring for radar band using convolutional DNN' which operates the measurement capable Devices (MCD's) to identify the radar signals in radio spectrum. The Deep learning framework includes Spectrum management systems with CNN updates and resolve the queries to MCD with acknowledge monitor report to management system. The LTE and WLAN systems are used for transmission tests with different performances metrics. The radio frequency interference (RFI) mitigation using convolutional DNN is presented in Aleret et.al [15], the U-Net is network architecture with extension of CNN with up sampling, down sampling and feature concatenation is incorporated to generate the segmented output for input data. The simulation and observation data of CNN is described with implementation for RFI mitigation.

The Schmidt et.al [16] presents the wireless interference recognition (WIR) with deep CNN, which learns its features through optimization process based learning process. The CNN targets to radio signals packet transmission with wireless technology like IEEE 802.15.4, IEEE 802.11b/g, and IEEE 802.1 for channel mapping and classification accuracy with different SNR for different wireless technologies are analyzed. Rajendran et.al [17] explains about wireless signal classification using DNN with low cost spectrum sensors. The modulation classification based on long short term memory (LSTM) is designed with Deep learning approach using phase and amplitude time domain samples. The modified Radio data set is used for LSTM Modeling. The classification accuracy calculation with SNR is done for LSTM model with similar approaches are tabulated.

The deep learning for physical layer is presented in o'shesa et.al [18] with different applications. The end-to-end communication systems in auto-encoders is described with simple transmitter, channel and receiver modeling along with two user interface channel modeling with minimizing the Block error rate (BLER) with respect to other similar communication systems. The radio transformer network is designed using DL approaches with BLER measurements. The Yao et.al [19] presents the unified DL approach for time series mobile sensing data processing. It address the feature and noise customization issues in unified manner. The challenging mobile sensing problems includes car tracking with monitor sensors, heterogeneous human activity recognition and user identification with biometric motion analysis with solving tasks are incorporated in single methodology.

The prior research studies mainly efforts in seamless wireless communication related to spectrum identification/sensing are dominantly based upon signal processing tools for wireless communication such as hybrid machine learning techniques like Support Vector Machine (SVM), K-nearest neighbors (K-NN), decision trees, deep neural networks and many more [20],[21-25].

III. PROPOSED SYSTEM

The problem of the signal identification, signal classification and the use of machine learning for this purpose is initially learned as a signal processing problem and it is being handled by the various digital signal processing toll boxes. The signal processing algorithms implementations of the signals manipulates various reasonable features and gives inaccurate results. To overcome this problem the solution strategies for the signal identification and classification evolved by combining the signal processing techniques with the conventional machine learning approaches like SVM, K-NN, ANN etc. But these learning approaches impose huge time complexities because of the processing operation of feature extraction as well as it is quite complex to identify the intrinsic features as it demands an expert domain knowledge. In the recent time the adoption of deep learning is found in the various other problem domain like image and speech recognition etc., that encourages the research community to exploit the benefit of such approach of deep learning in the domain of wireless communication for the task of signal identification and classification. The existing many approaches does not describe the mechanism adopted so that can be extended to the other types of problem as well they lack sufficient information of transformation process of how the wireless data can be represented. In order to further evolve the process this project aims to design a system of a framework to work with the wireless signal synthetic dataset and use the deep learning for the predictive classifier by exploring the processes of data handling, transformation, pre-processing, learning and training a data driven wireless signal deep learning approach for the predictive classifier as a multi-domain knowledge exploitation in the project including the knowledge of the computer science, understanding of the wireless communication, machine learning and signal processing so that this problem can be further evolved to meet the future demand of optimal spectrum utilities in the era of 5G communication with Internet of things(IoTs). In this chapter, a core components and the design strategies of the proposed project methodologies are described with the various software engineering design aids such as system architecture, process and data flow diagrams to described the system model and its behavior that initiates the thought process of well-designed modules , functions and procedures for the implementation of the proposed framework, and the benchmarking platform to validate the effectiveness of the implementation and method.

A. Core Architectural Modeling

The system architecture consists of four different computing layers such as i) Data Acquisition, ii) Pre-processing, iii) Classification and finally iv) Decision making.

The system is computationally designed in a way where in the preliminary stage of modeling it imports a specific type of modulation such as BPSK, QPSK, m-PSK, QAM or CPFSK and respective wireless signal data attributes with a flow of execution. During the modulated data acquisition and modeling, the wireless signal data and its corresponding attributes get digitized and quantized and finally the numerical representation obtained via analog-to-digital converters. The computation further perform summation on the quantized form of numerical signal attributes Q(t). Finally the wireless modulated signal representation is can be visualized. After the completion of data acquisition the computational efforts inclines towards pre-processing of the modulated wireless signal data. The process also incorporates a multiple filter stack features to construct a convolutional neural network form of structure. Here the upper bound of the selection of filter stack attribute is defined up to 4. Here each convolutional NN-stack can hold up to 100 features neuron set , thereby commutatively 4 different convolutional NN-stack feature neuron set can be all total of 400.

Further the time sampled data of modulated signal attributes are prepared and cleaned/transformed for deep learning and classification module. Thereby a training dataset is prepared for the classification of the features of wireless spectrum data. Finally using the feature label attributes the convolutional NN model predicts the pattern of signal spectrum and test the accuracy of using test data sets. Figure 1 exhibits the architectural schema of the overall system design.

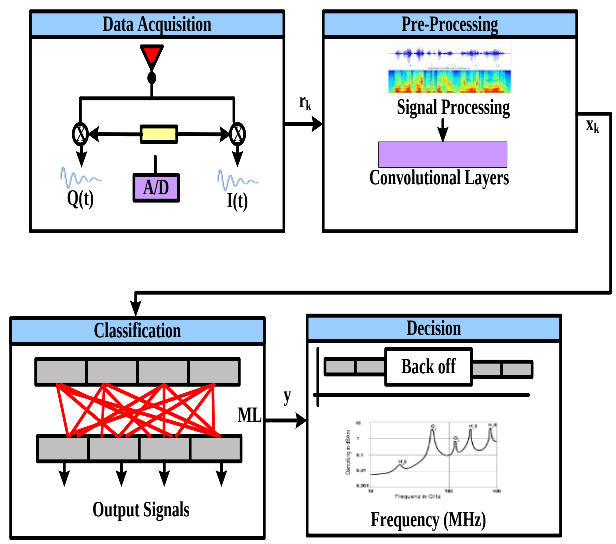


Fig 1:- Overall System Architecture of the Proposed Model

B. System Architectural Design

The system modeling basically operates on input modulated wireless signal data. Starting from data acquisition to classification and prediction of the spectrum attributes using convolutional NN feature stack set, the process involves end-to-end learning with significant convergence solutions. The system also incorporates wireless signal classification system and performance setup along with the convolutional NN training operations. The validation of the deep learning classification module is done by estimating the errors. The system architecture of the proposed model is described below in figure 2.

The final outcome of the modeling generates classification errors on the basis of learning and estimation of the predicted modulated spectrum data.

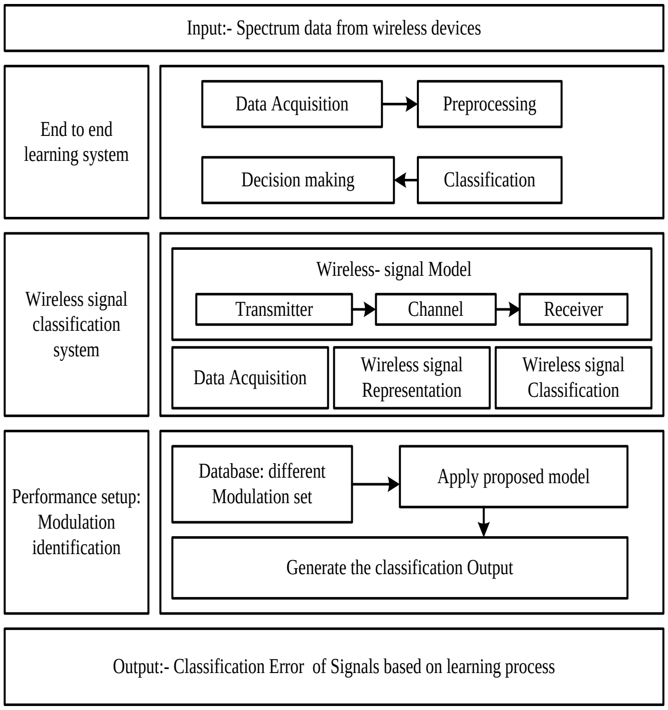


Fig 2:- System Architecture of the Proposed Model

➢ *Module one:*

Data Representation and Pre-processing. It is a well establish fact that the critical data is the enabler of the design principles of the various monitoring systems of wireless network to meet the intelligent system demand. In the real-time scenarios the logs created by the deployment of the various types of sensing process in the wireless environment and a raw format of the data is stored for the spectrum bands. In this project a synthetic data is taken for the representation of the spectrum data in the structure format. The data-store maintains a sample of various independent events of mixed modulation types of BPSK, QPSK, PSK, QAM and CPFSK in a stacking manner of one over another as a column vector as mixed data events from the revived wireless signal that acts as an input to the learning model for relevancy. The basic architecture of data receiving into the numerical computing environment is shown in the figure 3.

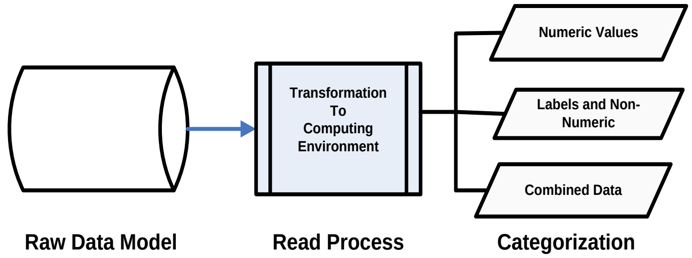


Fig 3:- Basic Model of the Raw Data to the Computing environment

The data receiving point of the wireless receiver or by the sensor in the wireless spectrum and communication is considered as wireless data point as a time stamping point. The modulated signal is derived from the categorized output of Numerical values of the transformation to the computing environment.

➢ *Data pre-processing Process flow:*

In this stage of the system design of data pre-processing the aim is for the better usage of the acquired data of the spectrum by achieving a better and qualified representation of the wireless signal data. The intrinsic data may include feature points of modulation type with its frequency, amplitude and the phase along with the feature extraction by the deep learning as various kinds of low- and high-level features to mimic the equivalence of the strong signal processing tools, to counter balance the choice of learning features and the choice of the machine learning models.

➢ *Process flow of Wireless Spectrum Signal Representation:*

The framework designed interface facilitates an user option to selected and visualize the selection of different signal formulation from the dataset Ds for the distinguished types of modulation schemes from BPSK, QPSK,m-PSK, QAM, CPFSK as a modulation set Ms ={M1 , M2 ,M3 ,M4 ,M5}. The data received by the wireless (sensor) is represented at variation time instance of Ts←WDp as wireless datapoint and the modulated signal (in figure 4).

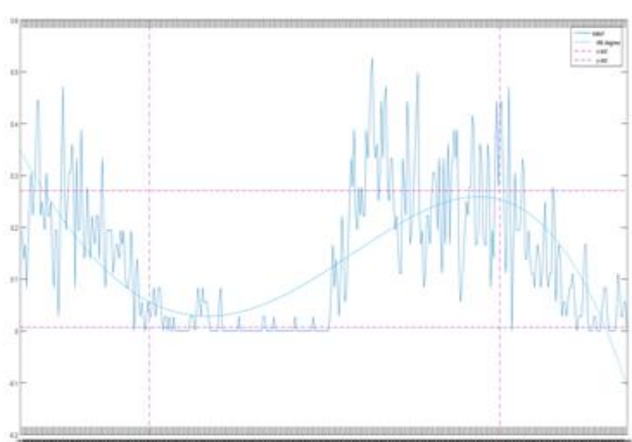


Fig 4:- Wireless signal spectrum representation after prepossessing

The following process workflow shows the computational execution flow to prepare the training data set for different modulated signal preprocessed time sampled data points.

Flow chart-1

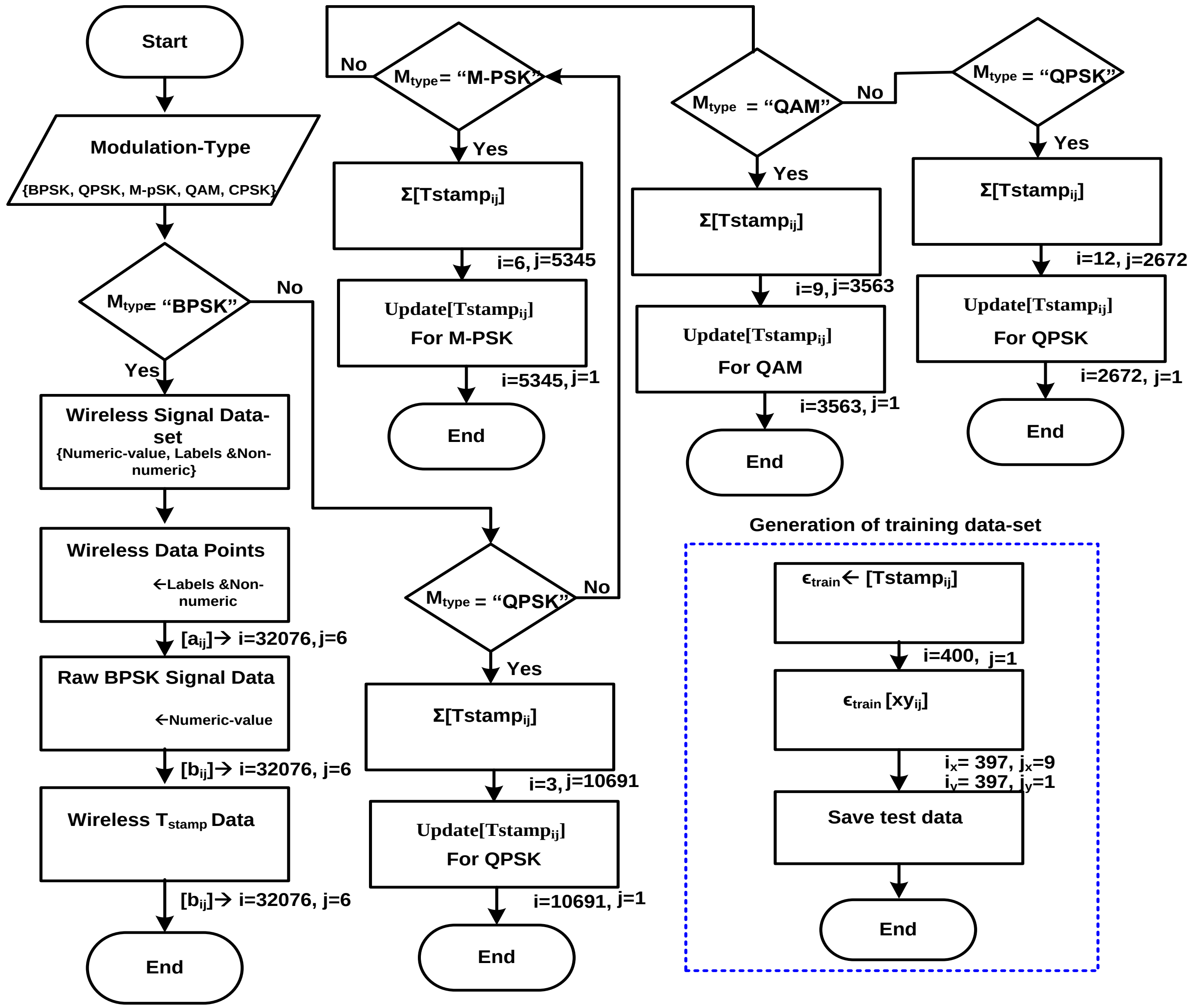


Fig 5:- Process flow diagram of the wireless spectrum signal formulation

Figure 5 shows that the workflow associated with the computational design of the deep learning module where the quantized form of wireless signal data is acquired, approximated with respect to numeric values, labels and non-numeric values. The further estimation of wireless data points further undergoes through a summation module where the numerical values are approximated and mapped with respective modulation schema. The numerical modulated signal values are further normalized to represent the digitized attributes between 0 to 1. Finally generation of training and testing data set is realized.

➢ *Deep Learning Module:*

To learn the features of Ts[i,j] wireless signal spectrum datasets which include both numeric values (NV) , non-numeric values along with labels , the model train , multiple Filter Stack using εtrain with deep learning. The convolution neural network consists of maximum 4 different filter stack where each filter stack consists of 100 of neurons. The following workflow shows the execution flow modeling to train convolution neural network CNN.

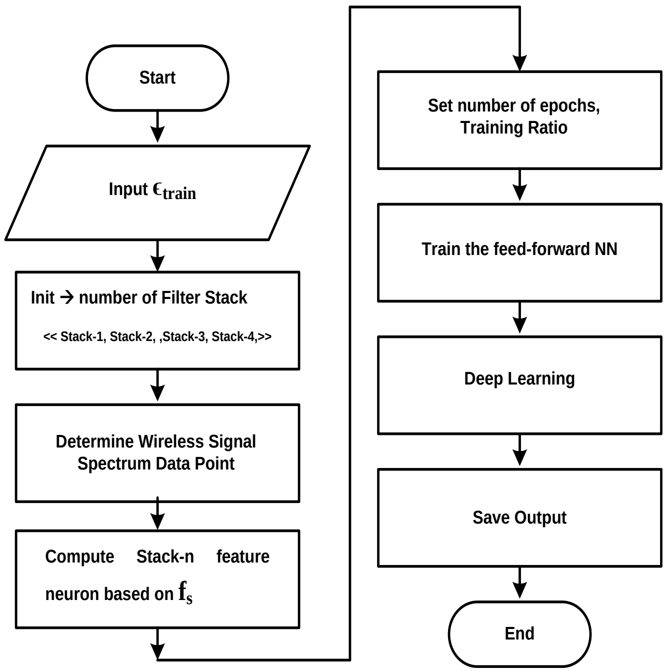


Fig 6:- Deep Learning and Training Module

The interpretation of Figure 6 clearly shows that how the feed-forward convolutional NN is trained in terms of training ratio, and stack-n feature vectors.

IV. RESEARCH METHODOLOGY

The computational design principle of convolutional neural network architecture is defined to predict the wireless signal data points from unknown spectrum. It basically imports a specific type of modulated signal and define multiple filter stack. Further the analytical modeling and design computes the ANN stack feature neuron set for 1→ 4 different filter stack input. Further the modeling generates a time sampled data set from wireless signal data for training. The labeled attributes are further used for proposed supervised convolutional deep learning modeling. The study also incorporated other two machine learning models such as i) Generalized regression and iii) Radial basis function which are also trained for the purpose of classification and prediction of the wireless signal data attributes. The figure 7 exhibits the process flow of the system model. The classification of the training features produces significant signal data attributes where distinguishing data pattern is simplified in the convolution neural network.

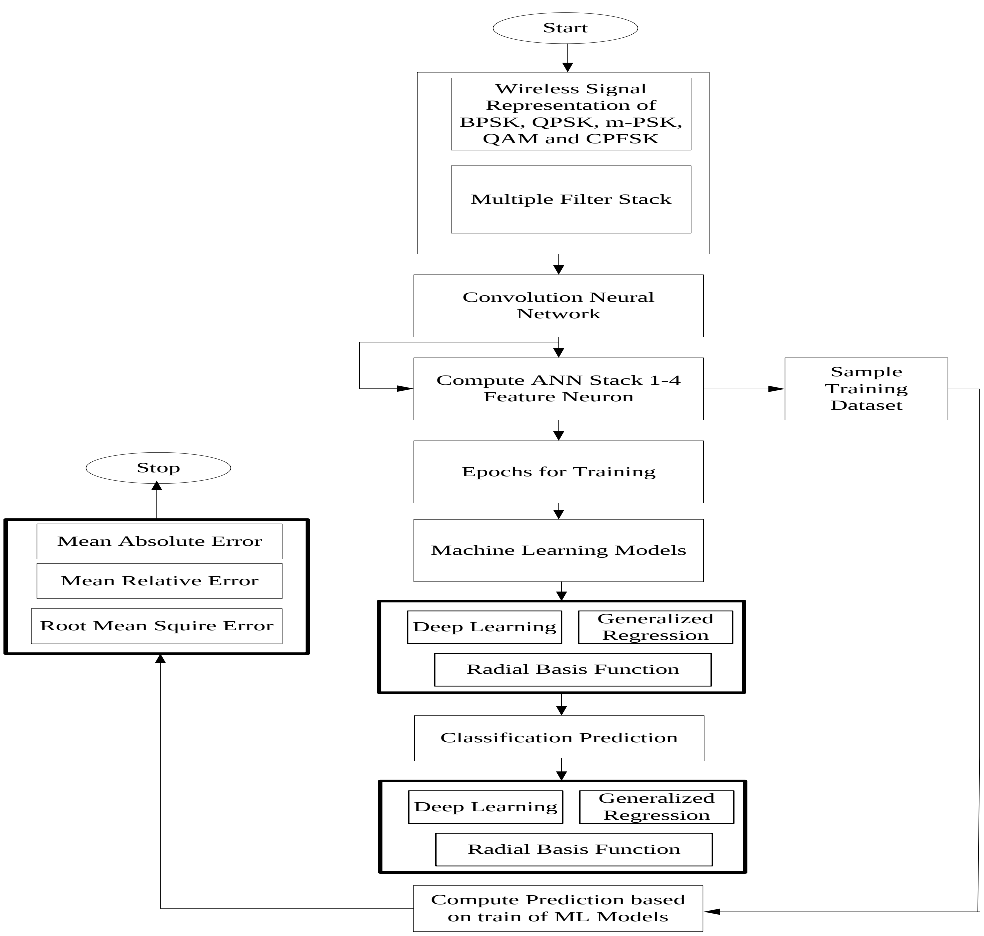


Fig 7:- Process Flow Diagram of proposed method

The trained output further compute the prediction modeling which is evaluated for three different ML models. The deep learning involves a set of ANN stack features to define the multiple filter stack of upper bound 4. The classification and prediction accuracy for different ML models are assessed. The wireless modulated signal spectrum data is determined using the proposed convolutional NN model and the model is further validated using a predefined test data set. The performance of the proposed model is evaluated in terms of Mean Absolute Error (MAE) , Mean Relative Error (MRE) and the classification error is computed by evaluating Root Mean Square Error (RMSE). The RMSE is computed by comparing the actual wireless signal spectrum data and predicted signal spectrum data.

The implementation scenario is carried out on a numerical computing environment where the minimum resource requirement to execute the i) Data acquisition, ii) Pre-processing , iii) classification prediction and iv) modulation identification requires minimum 64-bit operating system with 1.2 GHz processing and clock frequency.

The following are the execution steps defined for the proposed convolutional NN model to classify the wireless signal datasets cost-effectively.

➢ *Pseudo Code:*

Wireless spectrum signal formulation with modulated data points

Input: Select signal modulation type → Mt
Output: Generate → training data εtrain
1. Start
2. Get ← Mt wireless signal data
a. if (BPSK)
i. Get ←wireless signal dataset: {Numeric Value, Label & non-numeric values}
ii. Compute ←wireless data points {Label & nn}
iii. Compute ← Raw BPSK signal
iv. Compute ←wireless time-stamp Ts[i,j]
b. end
c. else if (QPSK)
i. Repeat → step a.i to a.iv for raw QPSK data extraction
ii. Compute Ts[i,j]
iii. Update Ts[i,j] ← $\sum$ Ts[i,j] where i→ number of rows and j→number of columns
d. end
e. else if((m-PSK)
i. Repeat → step a.i to a.iv for raw M-PSK signal data extraction
ii. Repeat → step c.ii and c.iii to update Ts[i,j]
f. end
g. else if((QAM || CPFSK)
i. repeat → step a.i to c.iii for computing Ts[i,j]
h. end
3. Compute εtrain ← Ts[ij] where i=400 , j=i
4. Save Test datapoints Tdata
5. end

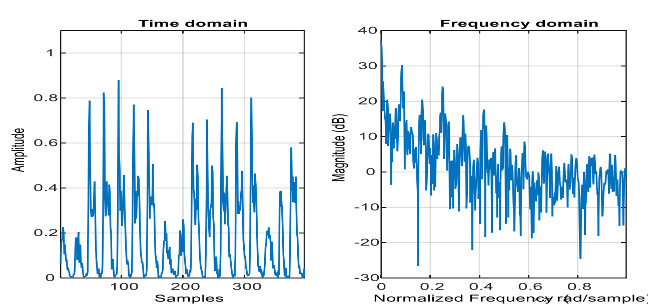
The above pseudo code shows how the raw modulated data got extracted in terms of value, label and non-numerical data and finally the signal representation with respect to Ts [i.j] is computed for a specific type of modulated wireless signal data such as BPSK/QPSK/m-PSK/QAM/CPFSK.

The system basically generated a synthetic wireless signal datasets which is formulated on the basis of channel impaired waveforms. The training data in this case also got generated using the Ts[i,j] vector of dimension (400 ×1). Prior training the convolutional NN, the software-defined modeling subjected to constraint the multiple filter stack with an upper bound of 4 stacks.

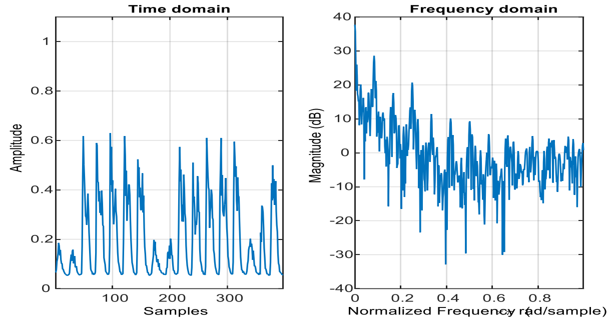
In each stack 100 feature neurons are defined. The following are calling and called methods to represent the modulated wireless signal datasets.

V. PERFORMANCE ANALYSIS

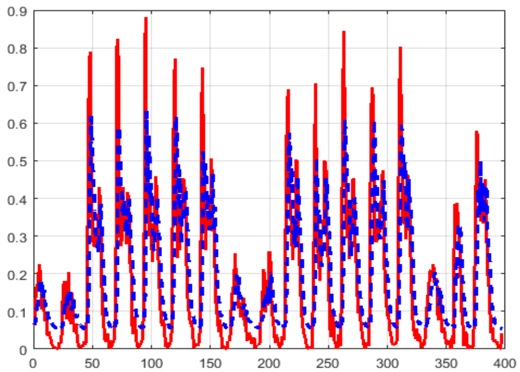
The framework of the deep learning model for wireless signal predictive classifier initiates with the sampling of the wireless signal data as synthetic dataset synchronous to the notion of the modulation process. The signal sampling takes up various kind of modulation scheme-based signal data that includes 1) BPSK, 2) QPSK, 3) m-PSK, 4) QAM and 5) CPFSK independently as a user choice in the interface. The signal is a function of the time(t) which is sampled at every five minute of time stamping interval as a data-point to the signal. The signal formulation indicates the varied mixed sampling of the various modulation scheme in the spectrum monitoring on the basis of classification by prediction. The heterogenous wireless network traffic over all duration includes as total dataset, out of which two third samples are taken for the training the model and one third is considered from the testing purpose. The network traffic composed of various other kinds of the signal feature collected at various data points that significances the synthetic reality to the real-time data set. Various kind of ambiguity in the spectrum monitoring arises due to mixed pattern of heterogenous modulation schemes that poses a non-linear and unreadable had condition on the classification. The figure 8 (a), 8 (b) and 8 (c) shows the signal representation at various modulation schemes like 1) BPSK, 2) QPSK, 3) m-PSK, 4) QAM and 5) CPFSK, respectively.



(a)



(b)



(c)

Fig 8:- a) Normalized frequency ,b) normalized frequcny for training data c) Pattern of training data

The above figure 8 shows the pattern of training and outcome of the training data. Which is obtained for 400 data samples.

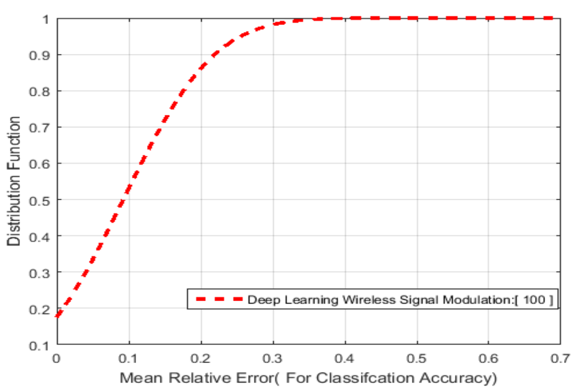


Fig 9:- Evaluation of distribution function

Figure 9 shows the pattern of evaluation of distribution fucntion with respect to the clasification accuracy.

The experimental outcome clearly shows that the formulated system attains better outcome as contrast to the generalized regression and radial basis function modeling.

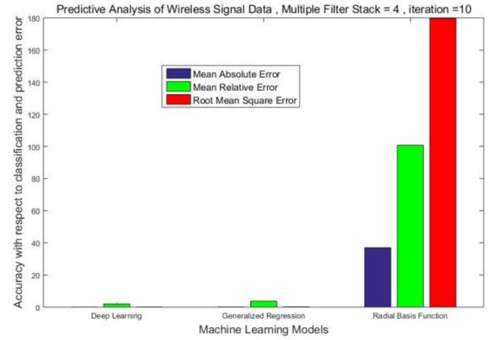


Fig 10:- Accuracy/ Error Estimation for different classifiers ANN stack filter = 4

The figure 10 clearly shows that the formulated convolutional deep NN performs better prediction to determine the data points in wireless signal spectrum that's why the analysis shows that error (%) is lesser in Deep learning model as compared to generalized regression and radial basis function.

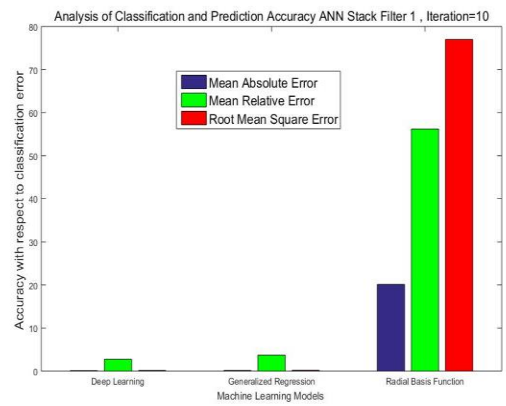


Fig 11:- Accuracy/ Error Estimation for different classifiers ANN stack filter = 1

Figure 11 also shows that the formulated deep learning model exhibits better prediction accuracy as compared to the existing baselines.

VI. CONCLUSION

The realization and advancement into the machine learning approach and data sciences has brought tremendous opportunities into building various intelligent applications in the field of the machine vision, automation etc. The exploitation of the machine learning into the filed of communication is quite new as well as challenging. This project is one of the approaches towards working on the wireless spectrum classification for the modulation schemes. A approach of deep learning is used for the learning model that is useful for the monitoring system of spectrum. The project methodology includes the signal formulation from the raw data of modulation. The convolutional neural networks

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(CNNs) is used because there are many features stacks of layers that are highly capable of processing and extracting the non-linear features of wireless signals correlated to the local and temporal variants of the spectra and it trains the wireless signal predictive classier in much better way to minimize the errors of the classification as compared to the existing conventional methods. This project design and implement a cross domain concept of the wireless communication, signal processing and machine learning context of usage of the deep learning for wireless signal predictive classification applicable for the monitoring of the spectrum. It elaborates the synthetic data mapping for the various signal identification.

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