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Machine Learning Based Localization Techniques

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Abstract

Internet of Things (IoT) is growing at a pace that can be called ubiquitous. IoTs can be nominated as a subfield of a superset known as Wireless Sensor Networks (WSNs). These sensors are used for remote monitoring, target tracking, efficient transportation, industrial monitoring, patient observation through physiological sensors, smart agriculture, smart homes, disaster monitoring and efficient management, and many other useful applications. Estimation of the location of wireless sensor nodes is known as Localization. Localization finds useful applications both indoors and outdoors. Different methods can be used to estimate the location; these include both range-based and range-free localization techniques. We apply supervised machine learning algorithms to estimate the performance of Localization using Received Signal Strength Indicator (RSSI) also known as Received Power, as a parameter for wireless sensor networks. The IEEECTW Challenge 2019 localization dataset for 1.25 GHz is used for training purposes. It consists of 16 elements of OFDM sounding data. The data set is collected through a massive MIMO channel sounder. Four algorithms are used for the purpose. The results show Mean Square Error (MSE) of Feed Forward Back propagation network (FFBPN) results in 0.41165 at 63 epoch, Cascaded feed forward neural network (CFFNN) gives 0.3953 at epoch 80, Elman back propagation (EBN) gives 0.38148 at epoch 20, and Nonlinear Autoregressive Network with Exogenous Inputs (NARX) gives 0.0042304 in 9 epochs. Hence, NARX performs the best among other algorithms.

Keywords: WSN, Machine learning, NARX, Localization, Artificial Neural Network

1. INTRODUCTION

The evolution of IoTs gives ad hoc networks remarkable attention to attain new avenues. The ad hoc networks can be distributed into two types i.e., Wireless sensor networks and mobile ad hoc networks (MANET). MANETs find their use in wireless mobile nodes, whereas wireless sensor networks are typically employed for static scenarios. As the use of wireless technology is progressing at a tremendously speedy rate hence the implications of ubiquitous connectivity also appears that exploits the use of IoT devices. The successful deployment of any wireless sensor network (such as IoTs) requires localization to be precisely estimated. Routing of information typically depends on the location information of sensors, hence accurate estimation of location becomes a mandatory requirement. Data transmission between any two nodes undergoes the routing step. Hence, successful communication depends on the successful implementation of the above steps. As the sensors operate in both indoor and outdoor environments so estimation of location is highly necessary. The outdoor localization techniques [1], mainly include Global Positioning System (GPS) based services and cellular communication-based services. GPS-based techniques are widely used in several outdoor applications; however, due to the requirement of a line of sight connection (LOS) with four satellites and higher power consumption, researchers [1], investigate other possible methods for better performance and energy efficiency. Hence, recommend a hybrid localization system for locating objects in outdoor environments. Additionally, in [2], the authors use distributed localization for outdoor terrain mapping through Extended Kalman Filtering. Furthermore, authors in [3], demonstrate the use of GSM cellular phones to secure the localization information and argue that the said scheme performs better both in coverage and accuracy. Based on the experimentation, it is shown that the GSM phone can achieve a 2-5 meter median error if the operating environment is indoor and a 70-200 meter median error for outdoor operating environments. The proposed experiments are not only limited to the GSM connection but to any active connection. The major challenge towards successful implementation of the said technique is the requirement of non-trivial training requirement of the system. In [4], the Authors recommend a localization technique for very small devices that cannot afford GPS in outdoor environments. In this scheme, RF-based localization is exploited. In this scheme, the receiver sensor starts localizing its position through nearby reference points using connectivity. Although the radio model used by the authors seems basic, it correlates well 87% with real environments.

Similar to the outdoor applications, indoor localization is also a key step towards successful deployment of sensors in different applications, including supermarkets, hospitals, warehouses, and surveillance and emergency response management systems. Besides, the fact that more than 70% of wireless communication is done through indoor environments hence the significance of localization in indoor environments is paramount in comparison to outdoor data transmission and other related scenarios. GPS-based localization is not a viable option for indoor applications, especially due to the weak signals and higher energy consumption[5]. Typically, Localization schemes can be distributed into two methods [6], these include Range Based Schemes and range-independent Schemes. Range-based techniques use a two-step method to perform localization. In the first step, the distance of the sensor is estimated with reference to the anchor node, and in the second step, an algorithm is applied to estimate the location of the sensor. Range-Based Schemes can be further divided into two schemes i.e., Distance Estimation and Position Estimation Algorithms. Distance Estimation Algorithms can be exploited using various parameters such as RSSI, Time of Arrival (ToA), Angle of Arrival (AoA), and Time Difference of Arrival (TDoA). Furthermore, position estimation techniques can be represented through Lateration, Triangulation, and Multi lateration. Range-based schemes can achieve higher accuracy however that is obtained at an additional cost of expensive hardware and higher power consumption [7]. However, given the limited availability of energy resources at the WSN, these techniques are not a preferred choice. Hence, Range-free localization techniques are preferentially used because these techniques do not require the estimation of distance as in range-based applications.

Received Signal Strength Indicator (RSSI) based Localization techniques find many applications in the area of localization, especially due to its easier implementation and cost efficiency [8]. However, the challenges involved with this technique include multipath fading and noise. As the wireless channel has a dynamic behavior, the accuracy and efficiency of these techniques typically cannot be assured.

Implementation of localization schemes can be done through various wireless technologies such as Wireless LAN (Wi-Fi), Bluetooth, Ultra-Wide Band technologies, Zigbee, Acoustic, ultrasound and Visible Light Communications[9].

In literature, there are many techniques that can be applied to localization data for the estimation of accurate results. These include deep learning and machine learning algorithms. These techniques can be further divided into three techniques that include supervised learning, semi-supervised, and unsupervised learning algorithms. Deep learning techniques find widespread use, especially in cases with large data sets. Additionally, the computational cost of these algorithms is also higher. However, machine learning techniques that exploit supervised learning techniques such as Artificial Neural Networks are computationally efficient algorithms with a lower number of implementation layers. Hence, ANN Algorithms are selected to deploy in applications that use IoTs. Due to the fact that IoTs are typically tiny devices and cannot afford to lose energy repeatedly during operation. The performance of four ANN-based algorithms is compared. The results show that NARX gives the minimum MSE among all other classifiers being tested. To the best of our knowledge, no previous work is available that exploits the algorithms considered in the paper on the selected IEEE CTW data set.

The abbreviations of the main terms used in the paper are summarized in TABLE 1

The rest of the paper is organized as follows. A brief literature review of ANN-based localization algorithms is presented in Section II. Section III presents the description of the proposed algorithms. Section IV presents the results and discussion. Section 5 concludes the paper.

Table 1: Table of main abbreviations

Abbreviation	**Description**
AI	Artificial Intelligence
ANN	Artificial Neural Network
CDNN	Cascaded Deep Neural Network
CFFNN	Cascaded Feed Forward Neural Network
CNN	Convolutional Neural Network
DL	Deep Learning
DNN	Deep Neural Network
EBN	Elman Back propagation
ENN	Elman Neural Network
FFBPN	Feed Forward Back Propagation Neural Network
FF-DNN	Feed Forward Deep Neural Network
GPS	Global Positioning System
GSM	Global System for Mobile communications
IoT	Internet of Things
KNNR	K-nearest neighbors Regression
LGBM	Light Gradient Boosting Machine
Lora	Long Range
LOS	Line of Sight
LPWAN	Low-Power Wide-Area Network
LSTM	Long Short Term Memory
M2M	Machine to Machine
MIMO	Multiple Input Multiple Output
ML	Machine Learning
MSE	Mean Square Error
NARX	Nonlinear Autoregressive Network with Exogenous Input
NLOS	Non Line of sight
OFDM	Orthogonal Frequency Division Multiplexing
RIS	Reconfigurable Intelligent Surface
RSSI	Received Signal Strength Indicator
TDoA	Time Difference of Arrival
ToA	Time of Arrival
WSN	Wireless Sensor Network

2. RELATED WORK

In this section, the related work of other researchers is presented. The authors apply ANN-based models to the localization database to produce exciting outcomes.

In [10], the authors use RSSI values of the sensor for localizing WSNs. Implementation and comparison of performance is carried through EBP, CFFBP, and FFPNN propagation neural networks. The Root Mean Square Error (RMSE) of Elman is 0.4991m, CFFNN 0.5257m and FFBP of 0.6506m. Hence, Elman performs better among the other algorithms.

In [11], the authors use an Elman neural network to estimate the coordinates using RSSI. The localization accuracy of 0.915 m is achieved. Due to the dynamic channel conditions, a high variability of received signal power is usually observed. Hence, to improve the accuracy of results, Kalman Filtering is used.

In [12], authors exploit RSS for localization; they have proposed a Feed-Forward Deep Neural Network Algorithm. The simulation results show 53.123% for the estimation accuracy of 0.5m, 78.123% for 0.75m, and 100% gives 1 meter.

In [13], the authors propose a cascaded deep neural network to investigate the system performance for localization. The researchers collect data through smartphones in an indoor setting. The results of the proposed study shows that a building, comprising of an area of 175 m2, an IoT object can be localized with an accuracy of 74.14% within a 1.5m radius, and an approximate accuracy of 53% is achieved within a 1 m radius.

In [14], authors investigate and compare the performance of various training algorithms based on Feed Forward Artificial Neural Networks for preparing and recommending a suitable framework for localizing the WSNs. The framework uses received signal strength as a parameter that is sensed by the anchor nodes in the given framework. The proposed network setup contains three-dimensional inputs. Additionally, one hidden layer is incorporated with a variable number of neurons. The network is designed with two outputs. Tansigmoid function is used for the hidden layer, while the linear transfer function is used for the output. Thirteen training algorithms are tested for this purpose. The algorithms use supervised based learning schemes.

Additionally, authors also recommend the use of a robust technique that uses a Multilayer Perceptron (MLP) that gives improved accuracy and precision for localization algorithms. Among the investigated algorithms, the Bayesian regularization algorithm gives the best results in comparison to other schemes, whereas Levenberg-Merquardt algorithm also produces better results. Besides, the Bayesian regularization algorithm requires a reduced number of computations to produce better results. Hence, the algorithm helps in saving essential computations by stopping the network from overtraining.

In [15], authors address the issue of the uplink localization problem in which a base station (BS) targets to locate the position of a remote user by exploiting reconfigurable intelligent surfaces (RISs). In this scheme, it is assumed that the remote user transmits beacons in a sequential fashion, and the Base station modifies the sensing vectors, including the BS beamforming vector and RIS coefficients, to produce an estimated user position. In this scheme, authors use deep learning algorithm, i.e. LSTM algorithm, to exploit the correlation between measurements to construct state vectors automatically. The results of the proposed setup show a tremendous improvement in the localization results. The proposed setup shows that a single BS with multiple RISs performs considerably better than the setup exploiting multiple BSs. After successful implementation of 5G wireless communications, the research and development now steps into 6G wireless communications to address the key challenges faced by this area. As the RIS is assumed to be one of the key components towards successful realization of next generation wireless radios hence, RIS technology will also play a role in localization and mapping of wireless sensor networks for the next generation radios. Simultaneous localization and mapping is attributed as the key technology towards localization, hence this setup proposes the absence of any Access Points from the proposed setup. Additionally, authors also derive the Cramer-Rao lower bound on the estimators for channel parameters and User equipment state. Additionally, the performance of the proposed algorithm proposed algorithm is evaluated under the case of limited number of transmissions by exploiting channel coherence time in consideration. In all the real-time implementation algorithms, estimation of localization typically results in several errors. In this research work [16], the authors exploit the use of machine learning algorithms to estimate average localization error in wireless sensor networks. In this research work, the authors use K-nearest neighbors' regression and light gradient boosting machine for this purpose. In this scenario, KNNRS proves to be a lightweight algorithm, while LGBM is an algorithm with computational complexity. Furthermore, authors also use the Walrus optimization algorithm to improve the performance of the proposed algorithms. The results of the proposed setup suggest that the LGWO performs better than other algorithms. The performance of the proposed setup is measured in MSE.

In the published literature, several other localization algorithms are proposed to identify the location information of wireless sensor networks as well as MANETs. A brief summary of research work done by other authors is also available in TABLE 2. In this paper, different classifiers for Artificial Neural Networks are proposed and implemented using MATLAB software. Additionally, the performance of these algorithms is also compared using MSE. These algorithms include FFBP, CFFNN, EBP, and NARX for localization. The data set is collected through a massive MIMO-based Software Defined Radio setup. The comparison of the results suggests the use of NARX in comparison to other algorithms.

3. MATERIALS AND METHODS

This work requires several steps to culminate and reach a point to produce the results. The proposed task starts with the collection of a dataset. As this is the key step towards the successful implementation of any project that involves learning based methods. This is done through using IEEE CTW dataset for the localization of objects. The second step involves the use of pre-processing of data. The third step is to select the artificial neural network-based classifiers for the prediction of parameters. The next step is to use hyperparameters to tune the algorithm so that it can produce the best results. In this work, Artificial Neural Network-based architectures are used to predict the results for the best possible cases. These include Feed Forward Back Propagation Neural Network (FFBPNN), Cascaded Feed Forward Neural Network (CFFNN), Elman Back Propagation Neural Network (EBPNN) and NARX. FIGURE 1 and 2 show a generalized and in-depth process of realization of the proposed network. A brief comparison of the results of these classifiers is also presented to identify the best possible classifier for applications such as the localization of wireless sensor networks.

3.1 ANN Training

Neural networks are attributed as the computationally efficient methods to represent knowledge of daily life examples, incorporating machine learning algorithms to compute results of high significance using different rules. The recent applications of neural networks in the medical, agriculture, manufacturing, engineering, and other sciences show a higher effectiveness as compared to one decade earlier. A neural network is a computational machine that mimics the role of biological neurons. Hence, a neural network is a model that is composed of artificial neurons. These neurons

Table 2: Shows a brief summary of related work

Reference	AI Paradigm	Algorithm	Objectives	Simulation/ Real Time	Results	Performance Metrics
[10], 2015	ANN	EB, CFB, FFB	To compare the performance of ANN Algorithms for Localization data	Simulation	MSE calculated for distance vector of 100m	MSE
[14], 2015	ANN	FFANNs-Back propagation	Improved accuracy and precision of localization algorithms	Simulation	Bayesian Regularization algorithm performs better than Levenberg Merquart Algorithm	Mean Localization Error for Network
[11], 2017	ANN	ENN	To improve the accuracy of localization data through Elman Neural Network	Experimental	Accuracy of 0.915m is achieved and it has good accuracy against RSSI variations	Absolute Mean Localization error
[12], 2018	DNN	FF-DNN	To improve localization estimation accuracy in localizing mobile users using RSSI and Deep Neural Network	Simulation	Improved Estimation error in localizing the mobile users for Deep Neural Network	RMSE
[13], 2019	DNN	CDNN	CDNN is used to accurately localize an object in an indoor environment	Experimental	Combination of Smart Phone Sensor Data and CDNN produces an accuracy of 53% for a 1.5 m radius and 53% approximately within a 1 m radius	Accuracy = No. of correctly classified instances * 100/ Total Number of instances
[17], 2022	EdgeLoc Model	CapsNET Model and Various others	Localization using RSS	Experimental	EdgeLoc gives minimum average Localization error in comparison to KNN, SVM, CNN, SAE-CNN	Average Localization error
[16], 2023	Machine Learning	Linear Regression, KNN and Decision Tree	Compared the performance of various ML algorithms on three different datasets	Experimental	Performance of Linear Regression is better among its competitors	Mean Absolute Error
[18], 2024	SLAM	SLAM for RIS	Localization and Mapping for wireless devices	Simulation	Improved performance of RIS setup through Localization and Mapping	Mean Absolute Error (MAE)
[15], 2024	DNN	LSTM and DNN	Active Sensing method is compared with deep learning algorithms	Simulation	The MSE appears to be lower for the proposed scheme in comparison to other deep learning models	MSE
[19], 2025	Machine Learning	K-nearest neighbors Regression (KNNR) and Light Gradient Boosting Machine (LGBM).	Proposed an algorithm that combines both KNNR and LGBM to improve the performance of localization	Simulation	The proposed technique performs better than algorithms applied separately	Average Localization Error

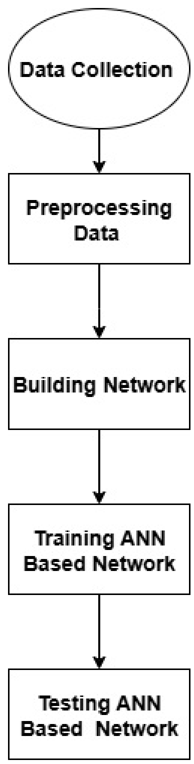

Figure 1: Shows a generalized network

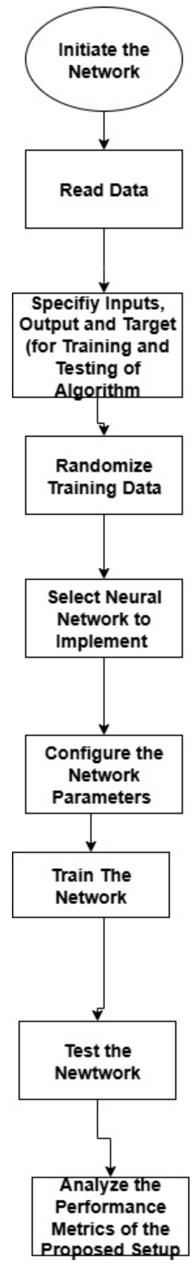

Figure 2: Shows step wise procedure for ANN network

are connected in such a way that each neuron gets an input from another neuron, computes some data or processes data in a specified manner, and then transfers the information to another connected neuron. And thus completes a processing cycle. Typically, these neurons are grouped in the form of layers. The first layer is known as the Input layer, the second layer is typically the hidden layer, and the third layer is known as the output layer. The most significant computations are performed by the hidden layers. Deep learning algorithms typically contain at least two hidden layers. As the significant computations are performed in this step hence the number of neurons and complexity of implementation may vary based on different applications. The hidden layer is implemented by incorporating weights and biases into the input data. The results are then processed through an activation function that introduces non-linearity. These learning based algorithms, also known as neural networks, can be categorized into four groups of algorithms. These include supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. In this section, a brief description of the training algorithms is presented, followed by the training results obtained from each algorithm. The supervised learning techniques are capable of producing exceptionally useful results based on learning the past data and producing meaningful results in the future by prediction. Though sometimes the data given to the algorithms is incomplete or erroneous, even then the predicted results are highly accurate. For this reason, these algorithms are widely used in several wireless communication applications that include classification, estimation, localization and prediction [20]. The unsupervised learning algorithms do not require any explicit labelled data rather look for undetected patterns in the given data. In this kind of network, the weights of the network are updated without the use of input-output grouping. The semi-supervised learning models use a mix of both labelled and unlabeled data to create a learning model for implementation. These models can be implemented through generative adversarial networks. Applications of these models can be found in data creation as well as audio-visual data manipulations. Another application of these algorithms can be invoked through self-trained naive Bayes classifiers that can be used for natural language processing. Another model type is known as the Reinforcement learning model. These models also recognized as self-interpreting models. These models typically execute on the basis of rewards and punishments, i.e. carrot and stick policy. The objective of these algorithms is to attain maximum possible rewards through trial and error. The examples of the algorithms include Q learning. This model is used for creating policy. Furthermore, another technique is known as model-based value estimation, which is used for linear tasks.

3.2 Working of the Proposed Network

Learning based algorithms are typically implemented through a flow chart as shown in FIGURE 1. The algorithm implementation is initiated with the data collection step. The data collection step is mostly implemented through sensors/detectors. The collected data is typically random and may comprise of many errors; hence, a preprocessing step is required to organize the data in a fashion that is amicable for the algorithm to process. The processed data is then sent to the ANN architecture for training and testing purposes. Furthermore, the algorithm can be elaborated as shown in FIGURE 2. This model shows the initialization of the project through network initialization. The data is randomized as shown to produce results in normal fashion.

3.3 Collection of Dataset:

Data set for training and testing is obtained from IEEE CTW 2019 Challenge 1.25GHz Localization Dataset, consisting of 16-element OFDM sounding data [21]. The data set consists of three variables i.e., channel responses, ground truth positions, and Signal to Noise Ratio (SNR) of the received signals. The dimensions of various variables are represented as h_estimated: [No. of measured data points x Antenna No.(10) x subcarriers No. (924)]. The variable h typically represents the channel response of that link. As the channel is dynamic hence on each step a different value is expected. The position is given with a variable r_position: No. of points and the coordinates [x,y,z]. The SNR: [No. of measured points x No. of antennas]. This data set was acquired using massive MIMO channel sounder shown in [15]. The channel responses were measured between the moving transmission setup and the 8x2 antenna array. As a transmitter, an SDR (Software Defined Radio) equipped vacuum cleaner robot was used, and it drove in a path on a 4x2 m table and transmitted uplink OFDM pilots with a bandwidth of 20 MHz and 1024 subcarriers at a carrier frequency of 1.25 GHz. 10% of the subcarriers were used as guard bands. The data set is trained using the Neural Network (NN) tool on MATLAB. Evaluation of performance is done by calculating MSE values. The parameters of the dataset are SNR and the position of sensors. SDR is an implementation architecture of wireless communication devices. The classic wireless transceivers were implemented through fixed hardware components. However, SDR architecture gives the user flexibility in implementation. The proposed system is defined and designed in software that is connected to hardware that implements the software routine. Hence, a single hardware can be used to implement multiple software routines. And these routines could result in different results. Additionally, the artificial intelligence-based algorithms can also be implemented into a software routine through software-defined radios. Such radios are called cognitive radios. These radios find applications in dynamic spectrum access, where a radio is allowed to operate on different spectral slots that are not used at a particular time instant, also known as white spaces. The sounding hardware typically transmits calculated waveforms in air with a receiver placed at a designated place that receives the pulses and calculates the response, and thus channel behavior is calculated. Hence, the channel can be predicted based on these calculations. The dataset is divided into half i.e., 50% data is used for training purposes and 50% for testing purposes. The models are simulated using MATLAB.

Feed Forward Back propagation Network [22], consists of three layers. These are represented as input, hidden, and output layers. The Back Propagation concept is used for processing the learning data set. In this network type, errors are transferred towards prior layers. Typical feed-forward networks consist of one or more hidden layers that use sigmoid neurons, which is connected with an output layer. Various number of neurons having nonlinear transfer function allows the network to understand both linear and nonlinear relationships between input and output connections. For getting a binary output from this setup, a sigmoid transfer function (tansig) is typically used.

A cascaded feed-forward network uses two links to connect an input layer of the network to an output layer of the network. These connections are direct and indirect. Besides a Direct connection between two layers, an indirect connection is linked through a hidden layer of the network. CFFBPNN is similar to feed-forward networks; however, it consists of a weight connection from the input to each layer and from each layer to the successive layers. Generally, two layers are sufficient to learn any relation between the input and outputs; however, more layers give the network enhanced efficiency towards learning complex relationships more quickly.

Elman Neural Network was first proposed by Elman in 1990. The algorithm was initially applied to audio data processing [23, 24]. It is a kind of dynamic recurrent neural network. This network model consists of four different layer types. These include an input, output, hidden, and context layer. The context layer serves as a feedback path from the hidden to the input layer. Context layer records data from previous network iteration as input to the current iteration. Hence, the Elman network works better in comparison to the other algorithms, especially for time series data. The output of the hidden layer at time t is given by:

$$y_j\,(t) = f\left(\sum_{i=1}^{L} u_i\,(t)\,w_{i,j} + \sum_{k=1}^{L} c_{k(t-1)} w_{j,k}\right) \tag{1}$$

The output of the context layer at t-1 time instant is given by equation (2)

$$c_k\,(t-1) = h_j(t) \tag{2}$$

In equation (1), $w_{j,q}$, $w_{i,q}$, and $w_{j,k}$ represent connection weights between the layers, as shown through subscripts respectively. In this equation, f represents the activation function. In the current scenario, the hidden layer takes a sigmoid function, represented through $f\,(x) = \frac{1}{1+e^{-x}}$ as activation function, whereas the output layer uses a linear function $f(x) = x$ as activation.

NARX is a type of recurrent neural network (RNN) model that consists of limited feedback connections as compared to other RNN architectures available in the literature. Hence, it is argued that these networks are at least equivalent to Turing machines, which means they can be used without any computational loss [20]. Additionally, it is reported that the gradient descent learning can prove to be more effective in these networks as compared to other RNNs [24]. A recurrent dynamic neural network consists of both feedback synaptic connections and delay elements that regulate the information flow through several sets of layers. Sometimes, recent past information is required, which is recalled through Recurrence (short-lived memory type). Delays provide information about the past events, whilethe feedback layer is used to perform filtering [22, 23]. The dynamic behavior of the NARX architecture can be modelled by equation (3) [25, 26]

$$y\,(i) = f\left[y\,(i-1)\,,\ldots\ldots.,\,y\left(i-d_y\right);;x\,(i)\,,x\,(i-1)\,,\ldots..x\,(i-d_u+1)\right] \tag{3}$$

where xi is the input function and yi represents the output of the given architecture at time i, while du < 0 and du = dy are the orders of input memory and output memory. NARX finds many applications in the given literature. These include predictor [27], classifier[25, 26, 28], also pattern recognizer. Furthermore, it can also be used in applications involving nonlinear filtering. In such applications, the target output is a noise-free version of the input signal.

NARX is a non-linear ANN network that is mainly used for time-series data. This network relates the current values of the time series to both past information same as well as exogenous input-output series [20, 29–31]. Exploiting the exogenous input-output relationships, this network can be applied for the prediction of time series. It is a computationally powerful tool that uses limited feedback. NARX is a widely used type of recurrent dynamic neural network. In this network, the output serves as input to the system. The computational dependence of the algorithm is based on output neurons. Hence, NARX models are considered to predict a wide range of nonlinear behavior. The architecture of NARX consists of three layers, namely input, hidde,n and output. Unlike other dynamic architectures like Elman and the layer recurrent network, no context layer is used in this scheme of neural network.

4. RESULTS AND DISCUSSION

In this section, the results of the proposed algorithms are presented. The Performance of the four algorithms is compared using Mean Square Error (MSE). MSE differentiates between observed values and the predicted values using the following equation:

$$MSE = \frac{1}{N}\sum_{i=1}^{N} e_i^2 = \frac{1}{N}\sum_{i=1}^{N} (y_i - \tilde{y_i})^2 \tag{4}$$

In the above equation, yi represents the observed output values, while the predicted values are represented by yi. Total values are represented by N. The best possible performance of the algorithms is represented by the minimum value of MSE. TABLE 1 shows the comparison of MSE values obtained through different neural networks. The results clearly advocate the use of the NARX algorithm in comparison to other algorithms.

By applying different algorithms, it is found that NARX is the most accurate of all four algorithms. It has the least mean square error among all. Its learning is much better and much faster than others.

The simulation of the proposed models is performed using MATLAB software. The best possible MSE results obtained from the ANN classifiers are obtained by the software and also indicated by the epochs. Hence, the minimum mean square results are obtained through the NARX algorithm with a minimum number of epochs, i.e., 9, in comparison to the other algorithms, as shown in TABLE 3, and FIGURE 3.

Table 3: Shows MSE and Epochs for different Architectures

Neural Network	**MSE**	**Epoch**
NARX	0.0042304	9
Elman	0.38148	20
CFFBN	0.3953	80
FFBPN	0.41165	60

FIGURE 3 shows a comparison of resulting mean square errors of various classifiers used in the proposed study.

FIGURE 4-FIGURE 7 show the MSE performance of various algorithms. The results show that the best performing architecture among the presented list is NARX, which achieves a MSE of 0.0042304 in 9 epochs. The next algorithm is Elman, which gives an MSE of 0.38148 in 20 epochs, while CFFBN shows an MSE of 0.3953 in 80 epochs, and FFBPN shows an MSE of 0.41165 in 80 epochs.

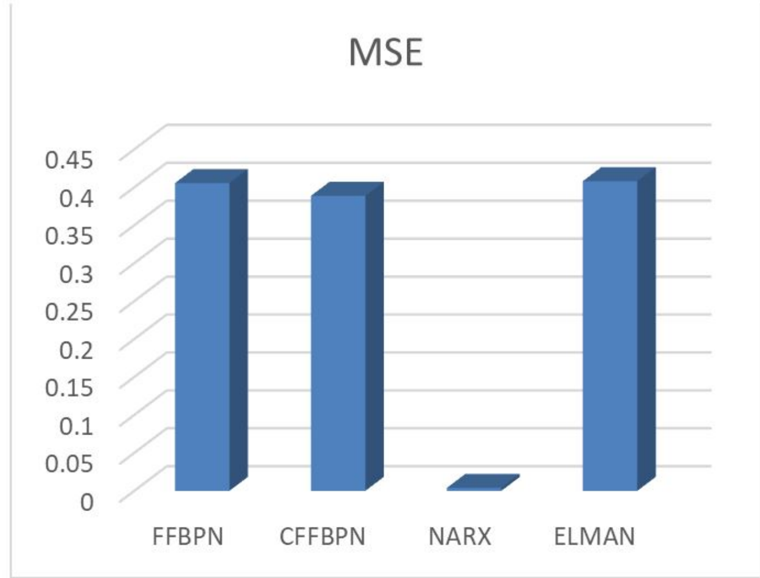

Figure 3: Shows a compassion of various classifiers for the proposed network

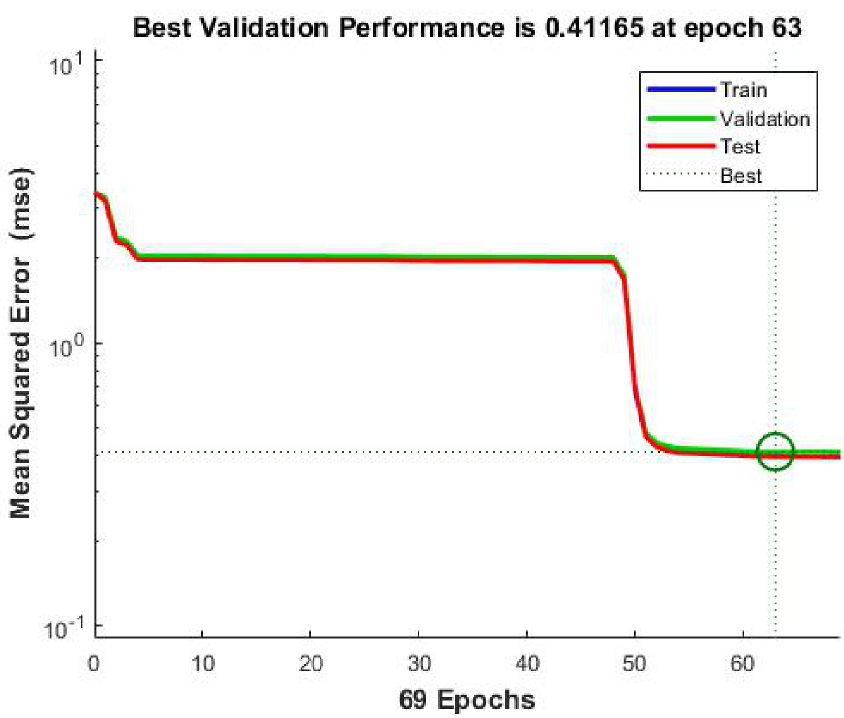

Figure 4: MSE plot of FFBPN

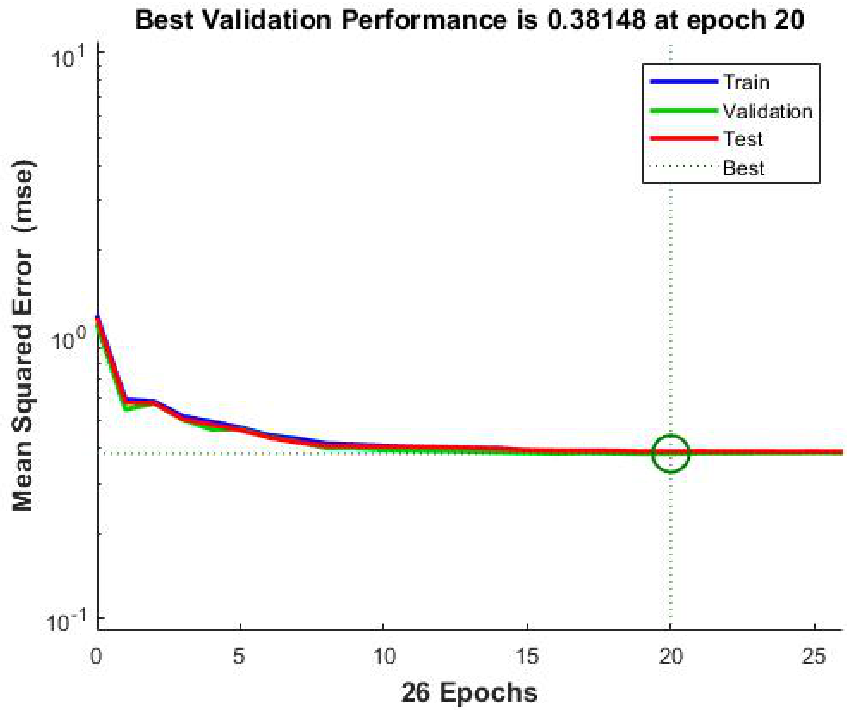

Figure 5: MSE plot of CFNN

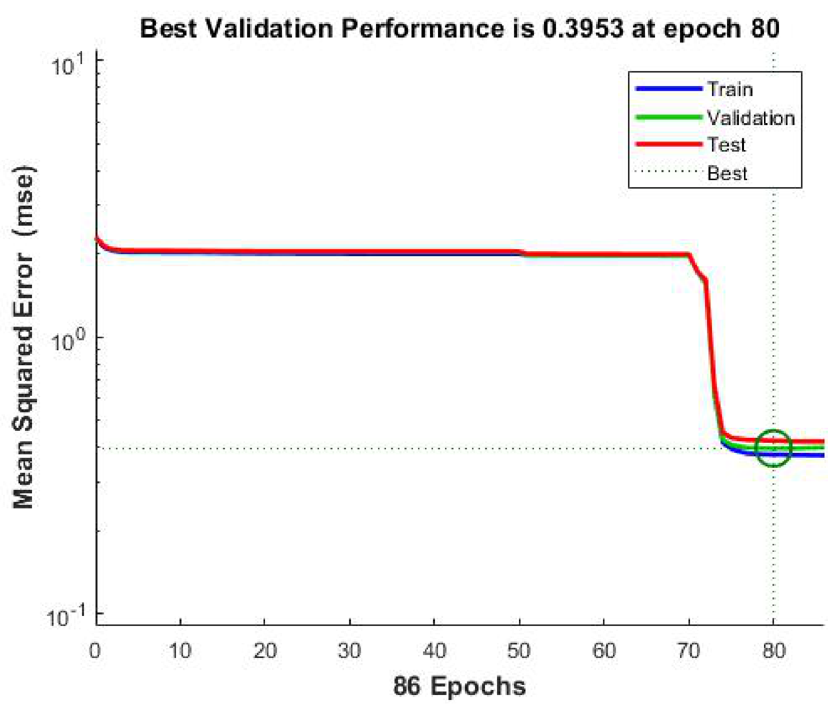

Figure 6: MSE plot of Elman Network

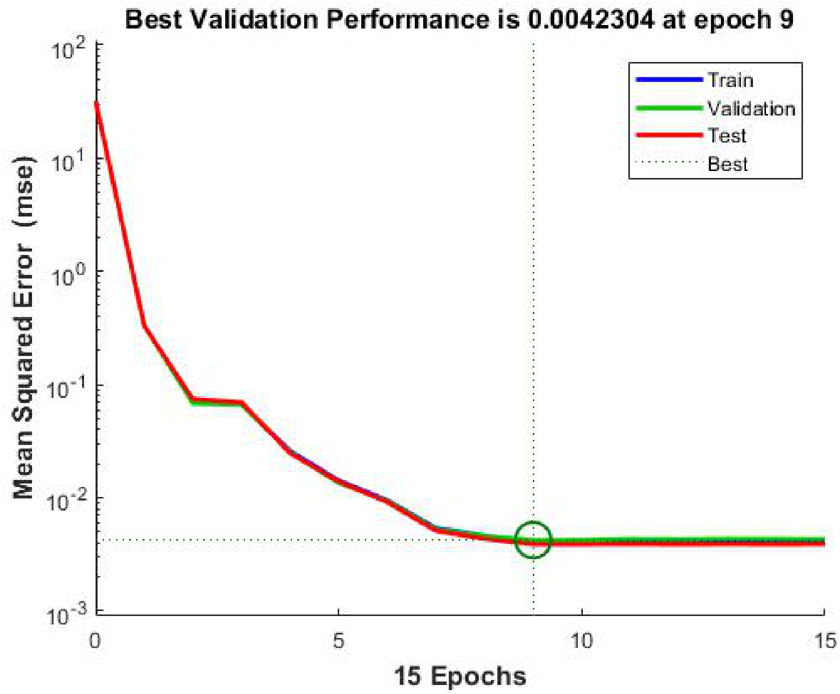

Figure 7: MSE plot of NARX Network

5. CONCLUSION

Four ANN architectures are applied to the localization problem. Localization is a key step towards the successful implementation of WSN in indoor applications. Four ANN architectures are employed under the data set published by the IEEE CTW 2019 challenge. This data set is collected through a massive MIMO setup for 1.25 GHz. Four Algorithms are considered for this purpose. These include NARX, Elman, CFFBPN and FFBPN. The best MSE is shown by NARX, which achieves 0.0042304 in 9 epochs. While the worst MSE is shown by FFBPN, which shows an MSE of 0.41165 in 60 epochs. Hence, based on the results, it is recommended to use the NARX algorithm among the list of other algorithms.

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