Deep Learning Enabled Spectrum Sensing Radio for Opportunistic Usage

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Summary
Radio spectrum is becoming overcrowded especially after the roll out of social media applications, live broadcasting, video calling and related applications. Additionally, under the umbrella of 5G and 5G+ wireless standards, these applications will require higher speed and higher bandwidth. Under the static allocation of frequencies regime, it is really difficult to accommodate the next generation users using the classic wireless technology. Thus, the current conditions in RF usage suggests the use of Cognitive Radio technology for using the RF spectrum in opportunistic fashion. This technology advocates the use of spectrum fashion such that the primary users are not faced with harmful interference. This paper presents the implementation of Deep Learning algorithm i.e. ADAM and Levenberg Merquardt algorithm (LMA) for prediction of spectral holes into Karachi city. Root Mean Square Error (RMSE) values computed for 1.9 GHz comes out to be 0.00063683 and for 3.4GHz the RMSE becomes 0.0010649, whereas RMSE for LMA is 2.91183e-03 at 1.9 GHz, appearing at epoch 5 and 6.0607e-3 at epoch 5 for 3.4GHz RMSE

Key words:
Deep Learning (DL), Machine learning (ML), Cognitive Radio (CR), Levenberg Merquardt Algorithm (LMA), ADAM

1. Introduction

RF spectrum Usage reports around the world show that most of the spectrum in desirable RF bands i.e. RF bands < 3 GHz is scarcely occupied [1][2]. Additionally reports show that there are a large of number of spectral holes that can be exploited spatially and temporally. However, due to exclusive rights of the primary users, no user can use the RF bands in time, frequency, code or space when no primary user or licensed user uses them. Cognitive Radio is a revolutionary technology that advocates the use of spectrum in secondary fashion [3][4][5][6]. However, the successful implementation of this technology depends on the accurate collection of RF environment data, such that the users with exclusive rights could not be facing the harmful interference from secondary activity also known as opportunistic users. Furthermore, the use of artificial intelligence enabled algorithms will make the process of RF environmental observation and predicting the spectral holes easier, autonomous and more accurate.

5G communication standard proposes connecting new devices and technologies at tremendously higher data rates. Many technologies will be included into this standard such as Internet of Things (IoT), Device to Device, Small cells, full Duplex radio, mm Wave radio, VLC and millimeter wave-MIMO, Cognitive Radio [7]. The authors have also presented the 6G vision that presents the enabling technologies such as Edge AI, Energy Transfer and Harvesting, communication with large intelligent surfaces, mobile millimeter wave technology [8].
These devices will produce enormous amount of data such that it is estimated that 50 billion devices will be connected by the end of 2020 [9]. Furthermore, only one of the technologies i.e. IoT, is assumed to generate extra revenue of $344B [10]. Thus it is anticipated that by 2020 IoT will have a 6% impact on the global economy i.e. $100 T. Thus, the use of the technological revolution suggests the timely exploitation of the 5G standard. Furthermore, the use Artificial Intelligence based algorithms will be highly useful in predicting the RF environment for possible opportunistic use in secondary fashion. These algorithms are initially trained in realistic environments and the results are stored to apply in unknown environments and predict the suitable results.
Typically, there are different types of algorithms used for separate set of applications. For example, supervised learning algorithms, semi supervised learning algorithms and unsupervised learning algorithms. The supervised learning algorithms work on the principle that the user has already got inputs and outputs. All required is to train the data so that the suitable decisions can be devised. The applications of supervised learning include classification and Regression.
Unsupervised Learning based algorithms have availability of inputs only. Thus, no association between inputs and outputs can be established a prior. Rather based on the data, further learning is done to produce desired results. Clustering and Association can be attributed as the key application areas to this set of algorithms. Semi Supervised Algorithms refer to the examples where only partial set of data is labelled and rest of the data is unlabeled, in such

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cases semi supervised algorithms are used. These algorithms come in between the supervised and unsupervised algorithms. In literature, several authors have used ANN based algorithms to devise suitable learning enabled results for different applications into Cognitive Radio domain [11][12].

As the wireless channel is a dynamic entity so it is often observed statistically that the received signal to noise ratio at the receiver is so week that most of the times the connection outages occur. Thus, making decision regarding presence or absence of a licensed activity under low SNR regime becomes a challenging issue. To mitigate the impact of low SNR, authors in [13] use wavelet transform and ANN to predict the presence or absence of user with more accuracy. Additionally, for better accurate detection, authors use cyclostationary feature detector. This detector detects the user based on the training sequences that embed cyclostationarity. Thus, the synchronizing sequences for different transmission technologies are different. The results show an improvement over the classical method of detecting the user under weak SNR case.

Typically the secondary use of Spectrum benefits a lot for the opportunistic users, however, the presence of attackers and malicious users also increases that try to interrupt the regular activity of primary or licensed users. In such environments, the primary activity becomes doubtful and it is difficult to operate the system on primary activity. In [14] authors investigate In authors apply spectrum sensing data to LMA to produce forecast results regarding presence/absence of a spectral hole for the purpose of secondary exploitation. The proposed method is called as Gravitational Search-Levenberg Merquardat (GS-LMA). The proposed method is also compared with Hidden Markov Model, Neural Network based techniques among others. The results are promising.

In Cognitive Radio. Spectrum sensing refers to the collection of RF environment data so that the secondary user can exploit it without harming the licensed activity. Typically, an alternative to this setup is the use of secondary broadcast stations. In that case, the availability of spectral slots is broadcast by the secondary base station so that the users can exploit is successfully. In [15], authors propose and analyze the performance of a hybrid spectrum sensing algorithm for opportunistic exploitation of RF spectrum in secondary manner. The proposed technique exploits Likelihood Ratio Test and Energy detection rules to measure the energy of the received signal and combine Artificial Neural Networks (ANN) for prediction. The proposed technique uses the energy received by energy detector and Zhang statistic and trains the ANN. The second step requires the decision making steps towards identification of unused spectral slots i.e. holes.

In this paper the RF spectrum occupancy data is collected using National Instruments USRP 2901 device and the data bank is used to train algorithms i.e. ADAM and Levenberg Merquardt Algorithm for predicting the RF spectrum results. So that the predicted results can be used to exploit RF spectrum in opportunistic fashion. Section II presents the proposed system model and section III discussed simulation results of the proposed algorithm for Karachi city while section IV presents the conclusion of the paper.

2. Machine Learning and Deep Learning Algorithms

Artificial Neural Networks are used to implement both machine learning and deep learning algorithms in practice[16]. Both of these set of algorithms are subset of Artificial Intelligence Algorithms. Machine learning is a branch of artificial intelligence which deals with the creation of algorithms which can modify itself without being explicitly programmed and learning from experience. Machine learning algorithms generally use structured data. Based on the key features of the data, labels are created and then they are used by machine learning algorithms for classification problem. In case of unsupervised learning, machine learning uses distance metrics to itself create labels whereas in Supervised learning, labels are created prior to passing them to machine learning algorithm.

Deep learning is considered a subset of machine learning where algorithms work similar to machine learning but there are numerous layers of these algorithms- each providing a different interpretation to the data it feeds on. Generally, Artificial Neural Networks (ANN) are used consisting of multi-layer environment as per requirement. The inspiration behind using ANN is to use human brain processing as benchmark for deep learning algorithm.

So, it can be concluded that there are significant difference exist between Machine Learning and Deep learning. One of the key difference between deep learning and machine learning is the representation of data. ML requires structured data whereas Deep learning algorithms require multi-layer data. Secondly, Deep learning algorithms do not require human intervention as nested layers work themselves to learn and produce output.

In general, as Machine Learning algorithms require labelled data, therefore, they are not considered efficient for complex problems but can work on less data as well. The Deep learning algorithms are heavily dependent on data, therefore, they require a large amount of data for obtaining reliable results. The reason is that multi-layer ANN relies on data for concepts, structures.

Additionally, Deep learning algorithms do not require structured or labelled data at the input to classify the given functions. Furthermore, these algorithms require different layers to covert the input into output data. Deep learning algorithms do not over fit the available training data. These algorithms take only a single dimension of data in raw form [7] . Additionally, these algorithms are more efficient to

segregate between different traffic classifications [17]. Furthermore, these algorithms provide accurate mobility prediction, capture the complex relationships among different data parameters without trying to over fit the data, perform better for large time series data and also preferred to be used under the circumstances where the implementation is required under imbalanced datasets. And these features are achieved at an additional benefit of less memory requirement and computational efficiency [7] .
On the other hand, machine learning algorithms use more than one dimension of data to optimize a parameter [7]. Additionally, implementation of a task similar to deep learning is difficult in machine learning. Furthermore, these algorithms are vulnerable to the over fitting of training data, contain lesser accuracy than deep learning algorithms and Levenberg Merquardt requires larger memory size to implement same task that is implemented using ADAM optimization schemes [18]. Additionally, these algorithms are typically not preferred for large data sets.
Machine learning algorithms can be distributed into two set of networks i.e. supervised and unsupervised algorithms. The supervised learning networks are started with training the system with data set. This procedure is also known as learning process. This problem can also be called optimization issue. There are many optimization problems that differ in speed and precision. These algorithms are required to minimize a loss function. The parameter used to compare the results of the proposed algorithm is Root Mean Square (RMSE). Loss function is tuned using adaptive parameters such as bias and weights. Levenberg Merquardt and Adam represent two separate families i.e. machine learning and deep learning algorithms [19].
Among machine learning algorithms Gradient descent works on lowest speed with consuming lowest memory, in comparison to Levenberg Merquardt, which performs the optimization at the fastest speed with highest memory requirements [20][21]. Most of the other machine learning optimization rules fall in between this range of principles.

Levenberg–Marquardt algorithm is a method to solve nonlinear least squares problems. The method is used to determine local minimum rather than global minimum. It achieves the result by interpolating between Gauss Newton and Gradient Descent formulas.

Adam Optimization Algorithm is also called as Adaptive Momentum Estimation Optimization method [19]. It is an optimization algorithm that can used to update network weights iterative based in training data. Adam optimization method uses adaptive weight update method to train the data. Adam Algorithm is a computationally efficient, low memory requirements. It is better for non-stationary objectives, can be applied for both noisy and sparse gradients. Additional benefits of using Adam optimization are easier implementation, efficient computation, and lesser memory requirements and preferred for use with large data sets and parameters. Furthermore, in terms of optimization, ADAM operates with the combination of stochastic gradient and RMSE propagation.

3. Performance Analysis of Proposed Model

Performance analysis is performed using two algorithms from machine learning and deep learning i.e. LMA and ADAM respectively.
The Figure 1 shows typical operation sequence of the proposed artificial neural network based ADAM optimization technique. The proposed setup requires the collection of Spectrum data. The spectrum sensing data is collected using USRP NI 2901 for two frequency bands i.e. [1] 1900 MHz – 1910 MHz and other [2] 3478.25 MHz - 3499.25 MHz the dataset was trained using MATLAB R2018a. The comparison of the DL and ML algorithms have been shown using RMSE.
The ADAM from deep learning algorithm is chosen and Levenberg Merquardt is taken from the family of machine learning. The following flow chart, Figure 1, shows the typically sequence of events to be executed for successful implementation of the proposed setup.
The proposed setup is implemented for two different frequency bands. The performance analysis of ML and DL algorithms is presented in the following graphs. The performance metric to compare the algorithms is chosen to be RMSE.

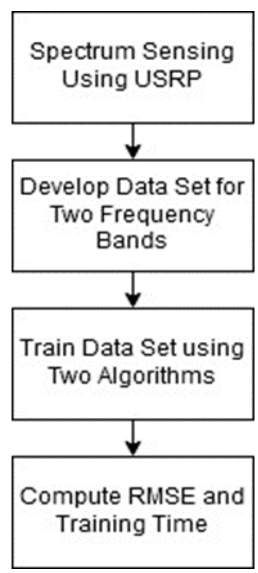

Fig. 1 Work Flow of Proposed Work

Figure 2 analyses the ML algorithm on band [1]. The figure shows the best validation performance appearing on epoch 6 with RMSE of 2.91183e-03 at 1.9 GHz and Mean Square Error (MSE) of 8.4788e-6.

Figure 4 shows the performance of ML on band [2], showing the best performance appearing on epoch 5 with RMSE of 6.0607e-3 and MSE of 3.6733e-5at epoch 5 for 3.4GHz.

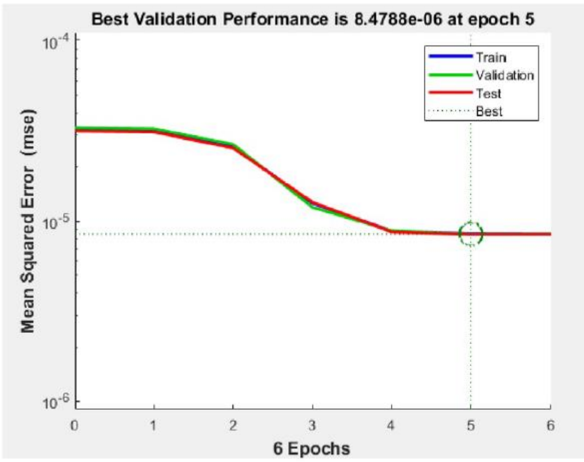

Fig. 2 shows the Testing and Validation of ML algorithm on Band [I]

Figure 3 and 5 show the performance of DL algorithm on band [1] and band [II] respectively. The RMSE values are show for the two cases. Additionally, more detail is also presented in Table 2.

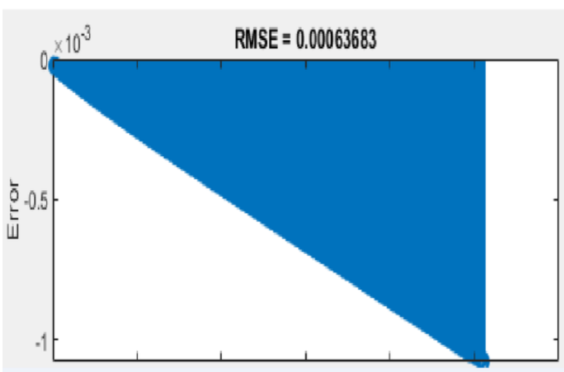

Fig. 3 Shows RMSE for DL on Band [I]

Figure 3 shows Deep Learning enabled ADAM Algorithm implementation on Spectral data bank prepared for Karachi city. The Root Mean Square Error for the proposed sensing band result into 0.00063683.

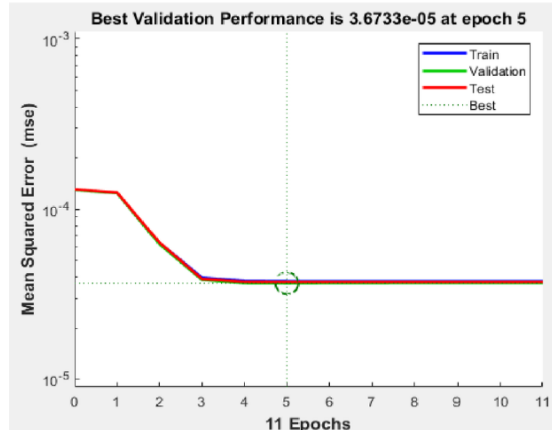

Fig. 4 shows the Testing and Validation of ML algorithm on Band [II]

Figure 4 shows the impact of applying machine learning based scheme to the II frequency bands. The results compare the training, validation, testing and the best available results through the available data.

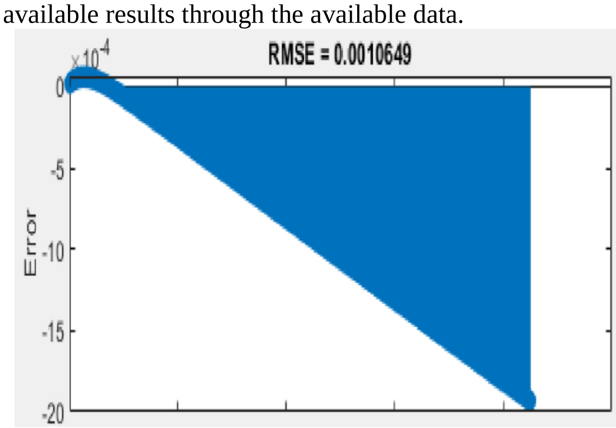

Fig. 5 Shows RMSE for ML on Band [I]

Table 2: compares ML and DL for two different RF bands.

	Band Type	**Number of input values**	**Training Algorithm**	**Max Epochs 1000**	**Training Time**	**RMSE= Sqrt (MSE)**
ML	[I]	10250	Levenberg Marquardt	1000/5	2 ms	8.4788e-06 MSE 2.91183e-03 RMSE
	[II]	21250	Levenberg Marquardt	1000/11	1 ms	3.6733e-05 MSE 6.0607e-3 RMSE
DL	[1]	10250	ADAM	1000/1000	20 min	0.00063683 RMSE
	[11]	21250	ADAM	1000/1000	49 min	0.0010649 RMSE

Table 2 shows performance analysis over two algorithms with RMSE and MSE. It can be seen from Table 2 that the Machine Learning algorithm does not reach the maximum epochs which has been set to 1000 and stops its training when it reaches the minimum gradient. Even though it takes very less time to train dataset which exposes it's to multiple dangers one of them is "over fitting" which can destroy the predicted result reliability. Further its RMSE value is greater than deep learning i.e. 2.91183e-03 and 6.0607e-3. On the other hand in Deep Learning it was observed that it takes more time to train dataset but completes its total number of epochs which has been set to 1000 which ensures the predicted result reliability by protecting it from over fitting and under fitting and also gives the less RMSE value i.e. 0.00063683 and 0.0010649.

4. Conclusion and Future Work

Performance analysis of ADAM (DL) and LMA are presented in this paper. The proposed algorithms are using RF spectral data bank prepared for Karachi. The data set is prepared using USRP NI 2901. Results show that RMSE of 0.00063683 and 0.0010649 were yielded and the least time of 5 msec and 6 msec taken by the deep learning algorithm. On the other hand, the RMSE numbers generated using LMA for band I and band II are 2.91183e-03 and 6.0607e-3 respectively. The comparison between the two algorithms for the given two bands show that the Deep Learning algorithm performs better for the both bands in comparison to machine learning algorithm.

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