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Spectrum Sensing in Cognitive Radio for Internet of Things using Deep Learning Models

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Abstract

An intelligent wireless communication system capable of learning from its surroundings is called cognitive radio. It permits Secondary Users to reuse the radio resources that are made available to them while avoiding damaging interference with licensed users. The key component of cognitive radio technology is spectrum sensing. The literature has become interested in the use of machine learning approaches for spectrum sensing. Enhancement of performance through further spectrum availability forecast and comprehension of the first activities of the primary user. Supporting many SUs at once will boost the speed of spectrum sensing and data transfer over the available, limited spectrum. The performance of current spectrum sensing techniques is constrained by severe channel conditions.With the advent of deep learning in various fields, we are trying to analyze the performance of spectrum sensing (SS) wherein deep learning method is adopted for data fusion. In this research, a data-driven deep learning model is suggested to automatically classify the received raw signal data, which is regarded as time-series data. In this paper, we have provided a comparative analysis of various deep learning models, including ResNet, VGG, LSTM, and MLP. The performance comparison was provided using various sample lengths and SNR values, both low and high. The ResNet model's performance has produced the highest detection probabilities in both low and high SNR ratios. The simulation result of the proposed methodology would improve the system's accuracy with a reduction in losses that occurred during the false alarm of prediction as well as an improvement in the probability of detection. Therefore, simulation results of the suggested methodology would lead to an improvement in the system's accuracy, a decrease in losses from false alarms of prediction, as well as an increase in the likelihood of detection. Better spectrum sensing would be achieved through deep learning's analysis of PU statistics.

Keywords: Cognitive Radio, Internet of Things (IoT), Spectrum Sensing, Machine Learning, Deep Learning, Probability of Detection.

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Introduction

Spectrum scarcity has emerged as one of the most significant difficulties facing the fifth generation (5G) of wireless communication networks as a direct result of the meteoric rise in the use of intelligent user devices, the Internet of Things (IoT), and autonomous vehicles. Cognitive radio is a promising technology that has the potential to increase spectrum utility.[1] It does this by allowing unlicensed users to take use of spectrum gaps in licensed bands while causing the least amount of interference possible to primary users (PU). One of the most important enablers of cognitive radio is the capability of perceiving gaps in the spectrum in an unfamiliar environment, which may include a number of primary networks. This enables cognitive radio to make use of the spectrum that is currently being underutilized.[2] Deep learning has demonstrated a powerful aptitude to discover complex patterns from raw training information without the necessity of removing hand-crafted features beforehand. This skill has been made possible by the rapid development of machine learning theory and the computational power available. Spectrum resources are becoming exceedingly difficult to come by due to the rapid development of wireless communication technologies and the introduction of 5G enormous multiple input multiple output (MIMO) systems.[3]

The introduction of the fifth-generation mobile communication network, also known as 5G, has been a major driving force behind the development of broadband wireless communication. Orthogonal frequency division multiplex, also known as OFDM, is one of the most common physical

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transmission technologies for wireless communication. The requirements of cognitive radio are partially satisfied by many of its properties (CR). The technology known as cognitive radio (CR) has recently emerged as a viable solution to the trade-off between the available spectrum and the increasing demand for it. Its purpose is to make opportunistic use of temporarily empty frequency bands, often known as spectrum holes or white spaces, in such a way as to guarantee that the licensed user would not experience any interference as a result of this practice.[4-6] Primary user (PU) is the term used to refer to the licensed user in the CR network, whereas secondary user is the term used to refer to the unlicensed user (SU). The fundamental idea behind coordinated re-use is to make it possible for momentarily unoccupied licensed bands to be accessed by SUs in an opportunistic way and does not cause interference.[7] This necessitates the development of spectrum sensing strategies that are both highly reliable and efficient. Cognitive radio, often known as CR, is a technology that was developed to make dynamic and effective use of frequency bands and is seen as a potentially effective solution to the spectrum problem. The core concept behind the CR is that users should have opportunistic access to the spectrum. When the main users (PU) are not actively using the spectrum, it enables the secondary users, or SUs, to perceive a gap in the spectrum and utilize the licensed spectrum band. Finding the unoccupied frequency bands that do not interrupt the PUs is an essential step in the process of achieving CR. Consequently, spectrum sensing technology has been suggested as a potential solution to this issue. Over the past few decades, numerous spectrum sensing approaches adaptable to a wide variety of contexts have been proposed. When it comes to semi-blind algorithms, in which the prioritized data of the noise power is already known, the traditional detectors are maximum eigen-value detectors (MED).[8]

Deep learning (DL) based algorithms, on the other hand, have demonstrated their major advantages in recent years, in contrast to model-driven based methods.[8-14] It can take advantage of the capabilities in various settings and is not constrained by the scene that was intended for it. A great number of algorithms based on deep learning have recently begun to build a name for themselves and offer exceptional performance.

In light of this, the paper propose using computational intelligence methods, such as the time-series deep learning methodology, to sense the available spectrum in 5G base transceiver stations. The system's architecture is meant to accurately forecast the amount of spectrum available without having any previous knowledge about primary users. After the implicit characteristics from the spectrum data have been extracted, the correlation between the historical and current data will be analyzed. This will be done in order to improve performance and decrease the likelihood of SUs colliding with PUs and other SUs.

Related Work

Transceiver stations at the base of a cognitive radio network employ a technique called spectrum sensing to locate unoccupied channels in the licensed spectrum of main users (PU) where data can be transmitted across a wireless network without being disrupted by other users. As the majority of 5G applications are dependent on wireless devices, the cognitive radio network was developed to solve the issue of a limited radio frequency spectrum. This was done in light of the fact that 5G was being developed. There is an improvement in the management of the spectrum for 5G thanks to the implementation of the idea of spectrum sensing.

The identification of spectrum availability emerges as the primary worry that this situation raises. Traditional methods can resolve this issue; however, they require a significant amount of effort and previous knowledge on PU and spectrum. This paper proposes using application computational intelligence algorithms (deep learning) for predicting the spectrum availability at 5G base transceiver stations because of their inherent capacity for learning.The ability of machine learning (ML) to perform complicated mathematical computations to evaluate and interpret models and data structures is one of the reasons it is becoming increasingly popular and being used in a wide variety of fields.

A deep-learning-based CNN-LSTM sensing detector, which employs the spectrum sensing method, was proposed by Xie *et al.*[1]. Conventional detectors include signal noise model assumptions, while the CNN-LSTM does not. Additionally, to reflect better detection performance, it learns the temporal PU activity pattern features and signal-energy correlation features at the same time. The CNN-LSTM detector is proved effective in both situations, i.e. with and without NU through simulations.

Meng et al utilized a deep learning generative adversarial network approach to recover the spectrum occupancy pattern for cognitive radio networks from sub-Nyquist sampled data.[2] Compared to traditional approaches, a performance gain of up to 14% was achieved through the proposed approach in predicting spectrum occupancy. The advantage of this approach is that the statistics of the radio environment are not required to be known to achieve the benefits. The performance of the algorithm is primarily determined by the neural network architecture utilized in DCSS-GAN.

Higher classification accuracy in comparison to IED and CED was achieved by Patel *et al.*[3] The artificial neural network for spectrum sensing designed in this work can learn the dataset's non-linear behavior. To improve spectrum sensing performance, the input features were given as previous sensing events, Zhang statistics of current, and energy. In addition to this, the optimal set of hyper-parameters, like activation functions, learning rate, and optimization techniques, were determined. Also, the evaluation of the proposed scheme was done and validated through spectrum data obtained through various radio technologies obtained with the aid of an empirical test-based set-up. The 40–60 model was employed to obtain the optimal set of hyper-parameters which furnished a commendable performance of ANN. The 40–60 model implies that around 40% of samples are acquired from the lower SNR values while the rest are acquired from the higher SNR values. The optimization algorithm employed is the Nesterov Accelerated Gradient optimizer, the sample size was N1/4 500 and the learning rate was 0.0001. Also, all four features (Zhang statistic of current, energy, and previous samples) were used to obtain the desired objective. The sample size could vary based on the application's system requirements. Once these parameters are set, an improvement in the performance of about 63% is achieved after the performance gain of all four RF technologies is averaged.

A cognitive radio spectrum sensing method that is based on deep learning and cycle spectrum is proposed by Pan *et al.*[4] for OFDM signal. The improved CNN model uses the OFDM signal cyclic spectrum as the dataset with the aid of which a spectrum sensing problem is converted into an image processing problem. With this, the powerful learning capability of CNN is better represented. Several simulations suggest that the proposed method is better in comparison to other machine learning methods. Also, the detection probability was found to be greater in comparison to the conventional spectrum sensing methods related to low SNR.

The temporal dependency in spectrum data is utilized by Soni *et al.*[5] Deep learning-based LSTM-SS scheme is proposed in this work that learns the prominent features in time series spectrum data. In addition to this, the PU activity statistics are also evaluated. For instance, duty cycle, on and off duration. Also, to optimize the sensing performance, a PAS-SS scheme is proposed. Both the schemes i.e. PAS-SS and LSTM-SS are analyzed and validated through the empirical data obtained from various wireless technologies from two test bed setups. As per the results, in comparison to the ANN-based hybrid sensing scheme, CED, IED, and even under the low SNR regime, the LSTM-SS proposed in this work has better classification accuracy and detection performance. The results from the experiments prove that when PU activity statistics are employed for sensing, a commendable improvement in performance is achieved. The performance improvement can be attributed to slight increase in execution time and long training time.

A deep learning-based spectrum sensing algorithm was proposed by Chen *et al.*[6]. To increase the quality of the sensing, a cooperative spectrum sensing system is introduced by the CSS-CNN algorithm. Also, the detection accuracy is improved by the utilization of CNN. The algorithm is extremely robust and has no sensitivity to noise uncertainty. In complex scenarios, the detection performance related to the CSS-CNN algorithm observes considerable improvement.

The performance of hard biased sensors related to off-tracking was studied by Liu *et al.*[7]. The focus areas include the sensor's magnetic noise and the effect of media's magnetic field on DC resistance. To consider the influence of local magnetic moment's non-coherent rotation, a model is put forward for reader resistance calculation. Through this, the reader's performance is effectively studied at off-track reading. The recording schemes like SMR and 2-DMR should appropriately account for the effect, particularly when head-to-media spacing is considerably small and the high coercivity medium is employed.

A deep learning technique-based method is proposed by Sundriyal and Baghel.[8] Compared to the conventional spectrum detection techniques, this has a higher accurate neural network exhibiting high detection probability. Therefore, concerning the detection time, the probability prediction for the main spectrum detection system remains very less. The technique possesses the speculation capacity and can accommodate itself to categorization of an assortment of undeveloped signs. The progress of identification is supposed to be around 0.995 for bogus alert likelihood.

For single-node spectrum sensing, a parallel CNN-LSTM was proposed by Xu *et al.*[9]. The complementarity related to the modeling capabilities of LSTM and CNNs is exploited by this network. In comparison to other spectrum sensing methods, like MME, ED, LSTM, and CNN, the performance over a high scale of SNRs from -20dB to 20dB is superior. This is suggested by the simulations. This shows, how effective is the parallel CNN-LSTM network. The detection of multiple modulation types can be accommodated by the CNNLSTM method, particularly under very harsh sensing conditions. The simulation data about the experiments was generated in this research article and better results were obtained.

A deep unsupervised learning-based detector UDSS was developed by Xie *et al.*[10] for spectrum sensing. No prior information related to the signal and noise distributions is required. A considerably lower amount of labeled training data is required by the UDSS when compared to the spectrum sensing algorithms based on supervised learning. As per the experiments, the non-deep learning algorithms are outperformed by the UDSS. Also, the performance projected is similar to the deep learning method considering CNN as the basis. In addition to this, appropriate verifications have been done for the UDSS algorithm pertaining to the non-Gaussian noise.

Sachi *et al.*[11] put forward a comprehensive channel model that represents primary factors influencing wireless communications, for instance, small and large-scale fading and path loss. The dataset pertaining to the received signal is synthesized as a set of SUs for a certain duration of time. The classification of the sensed PU signal is done through CNN as it is so subtle in its architecture. The classification accuracy is employed to evaluate the performance. Also, a comparison is made with various decision fusion-based CSS. A relatively higher noise floor is used to carry out the study.

The role of channel status to evaluate the performance of DSS with CR is analyzed by Usha *et al.*[12]. To deal with the obstacles pertaining to conventional spectrum sensing techniques, it is of utmost importance to involve ML algorithm in CR to optimize the learning process. To predict the channel state as busy, middle, and idle, a gradient boosting algorithm has been utilized in python. If 80% of the training set is considered, only 15% of it accounts for validation. Analyzing the results from simulations, it is observed that gradient boosting performs better. The accuracy of gradient boosting is about 99%. To avoid interference to PUs and save energy, obtaining the channel status information prior to everything else is beneficial.

Lie *et al.* put forward a big-data-based intelligent spectrum sensing.[13] The big spectrum data can be processed through ML and many available spectrum resources can be detected for heterogeneous spectrum communications. A CSSN is established so that WBSS could acquire big spectrum data. The spectrum data correlations have been analyzed in three domains: space, frequency, and time, to obtain a three-dimensional spectrum correlation. Also, to achieve real-time and accurate spectrum sensing, a novel dual-end ML model has been put forward. In addition to this, through heterogeneous spectrum data fusion and big spectrum data clustering. the estimation of the comprehensive state for the heterogeneous spectrum has been carried out. In the end, a few challenges about big spectrum data and some open research has been discussed.

Khan *et al.* propose to classify MUs and legitimate Secondary Users (SUs) a support vector machine (SVM) based algorithm.[15] Once the proposed SVM-based algorithm aids in classifying SUs and MUs, the diversified sensing reports obtained from the legitimate SUs are combined by the fusion center(FC) considering DS evidence theory as the basis. This could aid in making a general decision on the primary users' (PUs) existence in the network. The authenticity and superiority pertaining to the classification of the legitimate MUs and the SUs based on SVM have been verified through numerical results.

Methodology

The basic function of spectrum sensing systems is to detect the amount of accessible spectrum at base transceiver stations and determine whether or not the principal user is present. Because of this, there is a problem with keeping track of all of the channel information and spectrum properties to anticipate the available spectrum, Figure 1. A further problem that comes from this situation is the requirement for previous knowledge regarding primary users. The algorithms that make up computational intelligence can accomplish this goal. Here, we describe a model for spectrum sensing in CR-IoT networks that makes use of numerous antennas in conjunction with an observation vector, or Vn. This idea forms the basis of the spectrum sensing problem.

$$H_0: Y_n = U_n \qquad (1)$$
$$H_1: Y_n = h_n X_n + U_n$$

Where, H_0 = Hypothesis that shows absence of PU, H_1 = Hypothesis of the presence of PU, X_n = PU transmitted signal vector, Y_n = PU received signal vector, h_n= The channel index between PU and SU, U_n = Received noise.

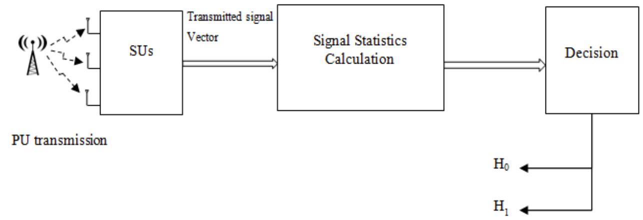

Figure 1: Conventional spectrum sensing.

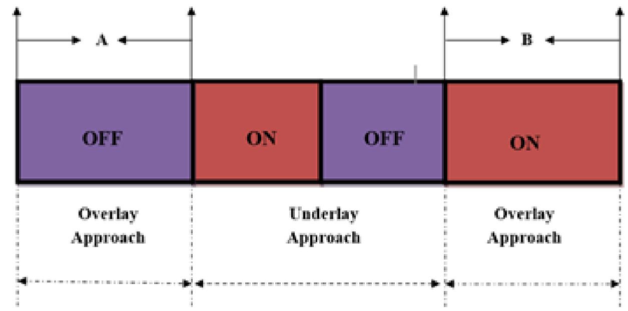

Figure 2: Activity Model of Primary User

An MIMO-based Cognitive Radio IoT model is proposed in this paper, with each user equipped with their own Tr receive and Tt transmit antennas and a central fusion antenna (FC). It has been decided that the CR-IoT user is analogous to an unlicensed user that makes incidental, non-interfering use of the PU's spectrum and that the PU is analogous to the licensed user of the spectrum. Most of the nodes in the network are PU transmitters and PU receivers. Ignore the fact that the PU is almost always authorized to use the channel. In Figure 2 we see the PU traffic over the channel. The PU's activity only modifies at the beginning of each time-slotted frame, indicating that the CR-IoT networks are perfectly synchronized or time-slotted. Due to the regularity with which a PU broadcasts packets with a fixed preamble, a CR-IoT may utilize this information to establish when the packet was sent, thereby allowing it to synchronize with the PU and sense the channel. The CR-IoT network is typically deployed with two major sequential links: one connecting the main users to the cognitive radio IoT user, and another connecting the CR-IoT user to the fusion center. As shown in Figure 3, all sensing functions are carried out by a deep learning module designed to improve sensing function.

This paper presents a DL-based secondary operator spectrum monitoring technique for cognitive radio networks. Without any previous information of the PU's signal or noise level, this technique uses unprocessed signal information. The spectrum monitoring technique consisting of offline instruction and online identification is shown in Figure 4. Initially, the training information gathered throughout the sensing procedure between both primary and secondary consumers is used to supervise the DNN presented. During online learning, the recently acquired signal information are used to train based on PU or SU presence. The PU is either existent or absent based on this probability. Furthermore,

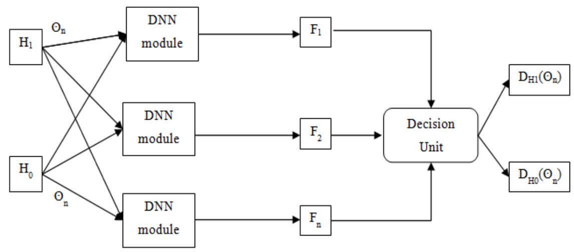

Figure 3: Deep learning based CR-IoT spectrum sensing

the suggested deep neural network framework, online identification module, and offline instructional module are each briefly presented.

Offline Training

In order to generate the instructional set of information for the suggested DNN, we categorize the acquired unprocessed signal information based on the conditions of H_0 and H_1.

$$(R,Z) = \{(R_1,Z_1),(R_2,Z_2),\dots\dots,(R_U,Z_U)\} \tag{2}$$

where (R_U,Z_U) denotes the ninth instance of the categorized instructional information set (R,Z) with u=1, 2,..., U; Ru is termed as the input information of N×2 vectors. The labeling for every Ru is denoted by Z_u∈{0,1}. The conditions of H0 and H1, however, are denoted by Z_u =0 and Z_u =1, respectively. Presence of PU is represented in terms of class as U. R and Z provide instructional scenarios under various SNR situations in this paper. In other words, following training, the suggested DNN can manage situations with various SNRs. As spectrum detecting may be described as a binary hypothesis assessment issue, researchers treat the offline instruction of the presented deep learning algorithm as a binary categorization issue. As a result, in the u_{th} scenario (R_u, Z_u), can also be transformed to a one-hot vector specified as:

$$Z_U = \{\frac{[1,0], H_0}{[0,1], H_1\}} \tag{3}$$

The presented DNN produces a vector of 21 category scores balanced by the softmax function as:

$$f_\theta(\text{Ru}) = \left[\frac{f_\theta|H_0\,(\text{Ru})}{f_\theta|H_1\,(\text{Ru})}\right] \tag{4}$$

With

$$f_\theta|H_0\,(\text{Ru}) + f_0|H_1\,(\text{Ru}) = 1 \tag{5}$$

Where θ and f (·) are the parameters and expressions of the framework. The assumptions' possibilities are expressed:

$$H_0 = Prob(Z_U = 0|R_U;\theta) = f_\theta|H_0(R_U)$$
$$H_1 = Prob(Z_U = 1|R_U;\theta) = f_\theta|H_1(R_U) \tag{6}$$

Where, $Prob\,(Z_U = i|R_U;\theta) = f_\theta|H_0(R_U), with\, i = 1$ or 0 is the conditional probability Prob $(Z_U$=i$|R_U)$ under θ.

Online Detection

After completing the offline instructional procedure, we acquire a well-trained DNN as described as:

$$f_{\theta^*}(R) = \left[\frac{f_{\theta^*}|H_0(R)}{f_{\theta^*}|H_1(R)}\right] \tag{8}$$

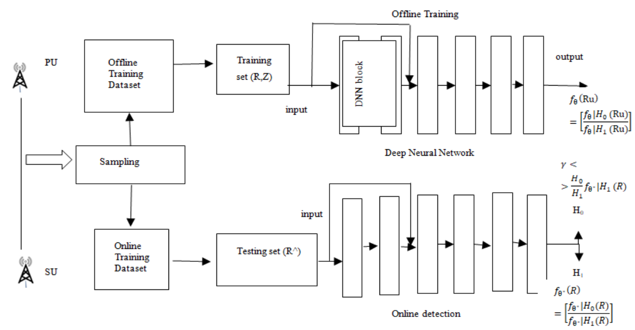

Figure 4: Offline and online spectrum sensing model

Where in fθ∗(·) and fθ∗|Hi(˜R) represent the well instructed DNN and Hi's class score, correspondingly. During offline detection process, unknown signal outcome is represented as:

$$\gamma <> \frac{H_0}{H_1} f_{\theta^*}|H_1\,(R) \tag{9}$$

We deduce the state (availability or non - availability) of the PU's signal depending on if fθ∗|H1(˜R) is higher than γ. In another terms, the group with the greatest category score is considered the ultimate categorization outcome.

Result Analysis

In this part, the effectiveness of the suggested model is confirmed by comparison to four other models. The dataset is generated with reference to.[16] We take into account Rayleigh fading and complicated AWGN while simulating channels. The PU signal data is produced using the GNU Radio, after the channel has been transmitted. In Table 1, important parameter settings are listed. A discrete time sequence made up of two components makes up our data. The first is the signals that SU receives while PU is present, or case H1. The other is what SU receives in case H0 when PU is not present.

Table 2 compares computation time for different methods in online and offline modes. MLP has an offline time around 0.53 and in online mode it is 56. Similarly, for ResNet it is 0.56 and online it is 65. For VGG it is 0.43 and online it is 69. For BiLSTM it is 0.67 and online it is 98. Table 3 shows the accuracy comparison of different methods in offline mode maximum accuracy is for ResNet *i.e.* 98%. For MLP, VGG, BiLSTM accuracy is 95, 96 and 94%, respectively. In online mode maximum accuracy is for ResNet i.e. 98 %. For MLP, VGG, BiLSTM accuracy is 92, 94 and 93%, respectively. Table 4 shows the

Table 1: Key Parameters and their values

Parameters	*Values*
Sample rate	200000 Hz
Sample per symbol	8
Sample length	64–512
SNR	[-20 0] and [0 20]db
Fading model	Rayleigh

Table 2: Computation time comparison of different methods

Methods	*Offline*	*Online*
MLP	0.53	56
ResNet	0.56	65
VGG	0.43	69
BiLSTM	0.67	98

Table 3: Accuracy comparison of different methods

Methods	*Offline*	*Online*
MLP	95%	92%
ResNet	98%	95%
VGG	96%	94%
BiLSTM	94%	93%

Table 4: Pd for Low SNR

Methods	*MLP*	*ResNet*	*VGG*	*BiLSTM*
-20	0.0798	0.103	0.09	0.0798
-15	0.157	0.2266	0.157	0.192
-10	0.439	0.338	0.419	0.409
-5	0.60	0.595	0.559	0.606
0	0.9811	0.9858	0.9811	0.981

Table 5: Pd for High SNR

Methods	*MLP*	*ResNet*	*VGG*	*BiLSTM*
0	0.994	0.995	0.995	0.995
2	0.995	1	1	1
5	1	1	1	1
10	1	1	1	1
20	1	1	1	1

PD for low SNR with different methods. For -20db SNR MLP has PD of 0.0798, ResNet has a value of 0.103, VGG has PD of 0.09, BiLSTM of 0.0798. Similarly for -15db SNR, MLP has PD of 0.157, ResNet has a value of 0.226, VGG has PD of 0.157, BiLSTM of 0.192. From these two we can conclude that as the SNR increases, PD also Increases. This pattern can also seen in VGG and BiLSTM. VGG PD varied from 0.09 to 0.9811 and BiLSTM PD varies from 0.0798 to 0.981. Table 5 shows the PD for high SNR with different methods as for Low SNR. In high SNR also, as the SNR increase PD also increases. For MLP it increased from 0.994 to 1; for the other three, it varied from 0.995 to 1. Our proposed work performs the best under all SNR conditions. Figure 5 shows the probability detection at Low SNR. Our proposed model shows the best performance with less SNR value as compared to the other models. Similarly, Figure 6 shows the probability detection at high SNR. The PD increases as the SNR increases for both the graphs. Figure 7 shows the online training loss of ResNet based spectrum sensing with different modulation scheme.

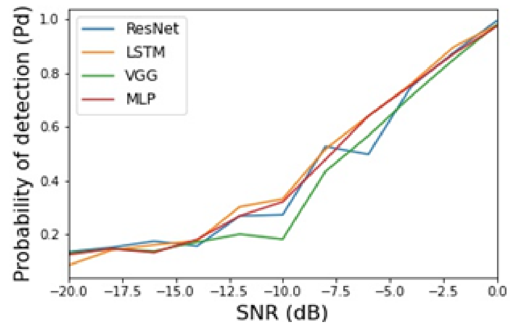

Figure 5: Probability of Detection at Low SNR.

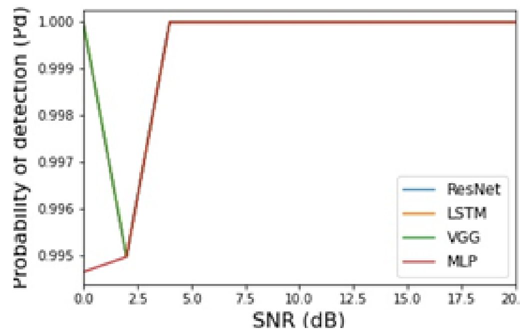

Figure 6: Probability of detection at high SNR.

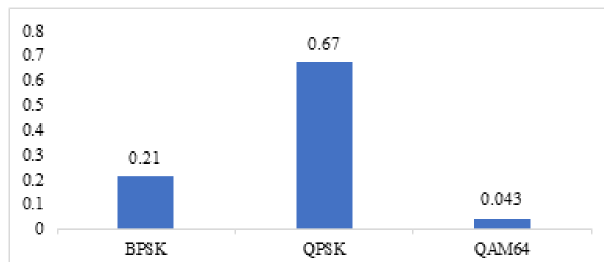

Figure 7: Offline detection error rate with modulation scheme.

Conclusion

This paper presents spectrum sensing model for 5G using deep learning techniques. In this paper we have presented a comparative analysis of different deep learning models such as ResNet, VGG, LSTM and MLP. The performance comparison was presented at low and high SNR values with different sample lengths. The performance of ResNet model have achieved best probability of detection in both low and high SNR ratios. The paper also investigated the probability of detection with different modulation schemes such as BPSK, QPSK, and QAM64. From result analysis it was seen that lowest offline and online error was achieved by QAM64. This shows the robustness of the system. In the future, we will investigate the model's performance under massive IoT architecture.

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