Machine Learning based Spectrum Detection in Cognitive Radios

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Abstract---Spectrum Sensing is considered to be most important characteristics of Cognitive Radio Environment. For most existing spectrum sensing techniques, the sensing performance heavily depends on the performance of these models. This leads to the problem of increased missed detection and false alarm which filters accurate utilization of spectrum. Recently, hawk-eye attention in the research of spectrum sensing algorithm is focused on the usage of artificial intelligence algorithms such as machine and deep learning algorithms. Therefore, deep learning based spectrum sensing minimizes the line of error in the detection of free spectrums. In this context, this paper proposes novel hybrid combination of Convolutional Neural Networks (RCNN) with the Reinforced Long Short Term Memory(R-LSTM) for the better usage of spectrums. The proposed system uses the Convolutional Neural Network (CNN) to exploit the energy features which are adaptive to the different modulations and signal to noise ratio models (SNR), which are used to train the LSTM for better detection of spectrums. The extensive experimentations are carried out using RadioML2016.10B datasets and various performance metrics such as Probability of detection, Sensing Error, Probability of Missed Detection, Prediction accuracy are calculated and compared with other state of art deep learning models. With an adequate simulations, performance of the proposed algorithm has shown superior performance over the other learning models.

Keywords— Spectrum Sensing, LSTM, Cognitive Radio

I.INTRODUCTION

Cognitive radio (CR) systems are a proposed solution to the spectrum scarcity problem in a radio frequency environment that aims to improve the overall spectrum utilization. Several studies showed that licensed spectrum bands are often not occupied by the licensed users, thus creating the opportunity for other devices to access the unoccupied spectrum opportunistically. These opportunistic devices denoted as secondary users (SUs) need to be able to sense the spectrum to assess the presence or absence of licensed users, denoted as primary users (PUs), either individually or cooperatively.

The idea of CRs was first introduced by Joseph Bitola III in 1999 but has been given much attention recently due to the proposed heterogeneous nature of 5G networks. Spectrum sensing in (SS–CRs) still poses a challenge for high performance and high-energy efficient systems since SS performance is often proportional to the spectrum sensing period. In turn, SS–CR is an energy-consuming task that also degrades the spectral efficiency of the SUs since they need to spend time and energy on a task that does not result in transmitted bits. Machine learning (ML) has received increasing interest and found application in many fields recently. ML is a way of programming computers to optimise a performance criterion using example data or experience. Such interest is due to its ability to apply complex calculations to evaluate and interpret patterns and to its ability to interpret patterns and structures in data, enabling learning, reasoning, and decision making. This apparent self-learning characteristic associated with ML techniques is by itself mostly based on applied statistics, whereas the training and inference capabilities owe their efficiency to great computer science algorithms .There are several networking open problems being treated under the ML perspective, including (a) traffic prediction; (b) traffic classification; (c) traffic routing; (d) congestion control, including important issues such as queue management, congestion inference, and packet loss classification; (e) resource management, which comprises admission control and resource allocation policies; (f) fault management; (g) quality of service and quality of experience management; (h) network security, aggregating anomaly, and intrusion detection; among others. A comprehensive survey on ML applied to networking is discussed in. Specifically, in the context of CR networks (CRNs), several research papers related to ML for SS have been published. These ML-based sensing techniques aim at detecting the availability of frequency channels by formulating the process as a classification problem in which the classifier, supervised or unsupervised

II.BASIC CONCEPTS

Spectrum sensing is a key function of cognitive radio to prevent the harmful interference with licensed users and identify the available spectrum for improving the spectrum's utilization.

A. COGNITIVE RADIO

Cognitive radio (CR) is a form of wireless communication in which a transceiver can intelligently detect which communication channels are in use and which ones are not. The transceiver then instantly moves into vacant channels, while avoiding occupied ones. These capabilities help optimize the use of the available radio frequency (RF) spectrum. It also minimizes interference to other user's .a, by avoiding occupied channels, it increases spectrum efficiency and improves the quality of service (Qu's) for users. The wireless RF spectrum is a limited resource, usually allocated through a licensing process. In the U.S it is the joint responsibility of the Federal Communications Commission (FCC) and the National Telecommunications and Information Administration (NTIA). The FCC administers the spectrum for non-federal (e.g., commercial) use, while the NTIA does the same for federal (e.g., military, FBI) use**.** The allocated (licensed) spectrum is not always used optimally. As a result, some bands are overcrowded (e.g., GSM cellular networks), while others are relatively unused (e.g., military). This spectrum inefficiency limits the amount of data that can be transmitted to users and lowers service quality as the number of connected devices in use continues to grow, this limited resource is fast becoming a *scarce* resource. Cognitive radio is an efficient way to use and share this resource intelligently, optimally and fairly.

B. COGNITIVE RADIO CHARACTERISTICS

Operating environment sensing: CRs operate in a multi-dimensional environment which can include cooperative or non-cooperative emitters that can toggle on and off, adapting to local changes as well as traffic loads which vary rapidly. In order to perform its task properly, a CR must change in accordance to the changing environment and it should be able to notify other devices in the network regarding the changed configuration. Operational state languages.

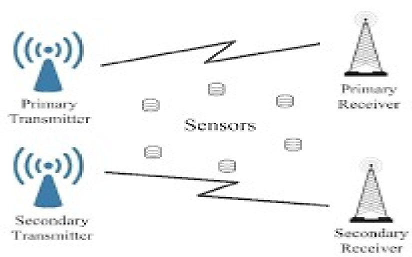


Figure 1: Cognitive Radio

Operational state languages are used for information sharing in a CR network. As mentioned above CR should inform its states and observations to other nodes in its network. The language that CRs use for this purpose is called operational state language. The information that a CR sends might be a list of all emitters that it recently sensed. Distributed Resource Management.

The radio spectrum is a distributed resource. Therefore use of a spectrum band at one location makes it unavailable elsewhere. Therefore the allocation of spectrum resources must be done in a balanced fashion. Various algorithms have been developed to handle the allocation and managing the distributed spectrum and resources based on traffic loads.

C. COGNITIVE RADIO FUNCTIONS

Spectrum Sensing: In order to avoid interference the spectrum holes (bands not being used by the PUs) need to be sensed. PU detection technique is the most efficient way in this respect. The spectrum sensing techniques are basically divided into three categories, which are transmitter detection, cooperative detection and interference based detection.

Spectrum Management: There is a need to capture the best available spectrum to meet the user communication requirements. CRs should decide on the best spectrum band to meet quality of service requirements over all spectrum bands. The management function is classified as spectrum analysis and spectrum detection.

Spectrum Mobility: It is the process where a CR user exchanges the frequency of operation. They target to use the spectrum in a dynamic manner by allowing the radio terminals to operate in the best available frequency band. The shift to a better spectrum must be seamless.

Spectrum Sharing: It is of utmost importance to provide a fair spectrum scheduling policy. It is also one of the most important challenges in open spectrum usage. In the existing systems it corresponds to the existing MAC problems.

D. COGNITIVE RADIO ARCHITECTURE

A Cognitive radio network consists of primary networks as well as secondary networks. A primary network comprises of one or more PUs and one or more primary base station. The PU's are licensed to use the spectrum

and are coordinated by the primary base stations. PU’s communicate among each other through the base station only. Generally the PUs as well as the primary base stations do not have CR properties.
On the other hand, a secondary network comprises of one or more SUs and may or may not contain a secondary base station. For SUs, the spectrum access is managed and handled by the secondary base station which acts as a hub/access point for the SU network. The SUs under the range of the same base station communicate with each other through the base station. If more than one secondary base station shares a single spectrum band then their spectrum usage and coordination is done by a central spectrum broker. A set of SUs can also connect to each other and communicate among themselves without the presence of the secondary base station. This kind of network is called an ad-hoc network. Internet of things (IOT) as well as vehicular ad-hoc network are some of the examples.
As the SUs should not cause interference with the PUs transmissions, all the SUs along with the secondary base stations are equipped with the CR properties. So whenever SUs detect the presence of a PU in a spectrum band they should immediately stop using that band and should move to some other available band to avoid interference with the PU transmission.
Spectrum band consists of licensed as well as unlicensed bands. PUs are authorized to use the licensed bands while the SUs can only use the licensed bands when the licensed bands are idle and are not being used by the PU. If a PU starts using the licensed band on which a SU is transmitting, the SU should immediately Detect PU's presence and should stop transmitting on that band and should move to some other available band. The information regarding the available bands as well as the occupied bands is provided to the SUs by the secondary base station. The secondary base station is supposed to handle the band allocation and maintain coordination among all the SUs within that network.
Whenever a SU detects the presence of a PU, it sends this information to the secondary base station and the secondary base station then informs all other SUs regarding the presence of PU on that band and asks all the SUs to give up that particular band. If SUs reusing an unlicensed band then they can form an ad-hoc network and can coordinate among themselves without the secondary base station?

III. *EXISTING SYSTEM*

The existing works can be classified into two main categories. The technique in the first category uses two steps. In the first step, unsupervised ML techniques are used to analysis data and discover the PU's patterns. In the second step, supervised ML techniques are used to train the model with the data labelled in the first step. For instance, a two-step ML model for SS can be constructed. In the first step, for instance, the K-means algorithm could be used to identify the state of the PU's presence. In the second step, support vector machine (SVM) or other types of classifiers can be used to attribute the new input data into one of the classes specified by the K-means method used in the first step.
Techniques of the second category assume that the classes are known, and they are based on supervised ML to train models. In the current work, we follow the second category approach. For example, existing works in the literature that use only one step in which supervised ML classifiers, such as K-nearest neighbor, SVM, Naive Bayes (NB), and decision tree, are applied. Since the task of determining the channel status based on SS is due to its nature a classification task, several authors have considered the use of ML models as inference tools.

In, the authors propose and compare the performance of several supervised and unsupervised ML techniques for cooperative SS purpose, such as considering distinct training set sizes or different channel scenarios of practical interest in, the authors study the use of ML algorithms for spectrum occupancy in CRNs, which include the Naive Bayesian classifier. In, the authors propose user grouping algorithms to improve SS results and SVM training time and in the authors enumerate the pros and cons of several unsupervised and supervised ML techniques applied to SS, such as the requirement of data labelling for supervised models and the risk of over fitting. Shah and Koo proposed a centralized SS–based on K-nearest neighbor. In the training phase, each CR user produces a sensing report under varying conditions and based on a global decision either transmit or stays silent. The local decisions of CR users are combined through a majority voting at the fusion center and a global decision is returned to each CR user, implying in a spectral overhead.
The SVM-based cooperative SS model with the user grouping method is discussed in. User grouping procedures reduce cooperation overhead and effectively improve detection performance. Hence, users in CRN are grouped before the cooperative sensing process using energy data samples and a proper ML model. The authors compare three grouping methods, the first divides normal and abnormal users into two groups, while the second grouping algorithm distinguishes redundant and no redundant users, and the third grouping algorithm selects users within a subset that minimize average correlation. The performances of the three algorithms were quantified in terms of the average training time, classification speed, and classification accuracy.

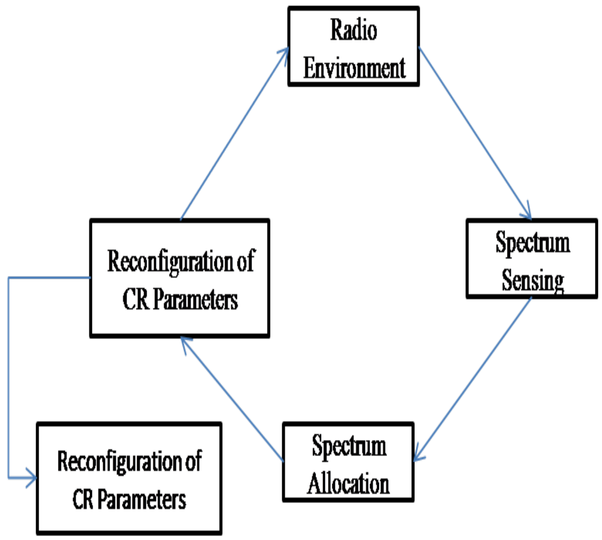


Figure 2: Existing System

This existing system presents cognitive radio (CR) is a form of wireless communication in which a transceiver can intelligently detect which communication channels are in use and which are not. It instantly moves into vacant channels while avoiding occupied ones.

It does not cause any interference to the licensed user. Cognitive radio (CR) technology is envisaged to solve the problems in wireless networks resulting from the limited available spectrum and the inefficiency in the spectrum usage by exploiting the existing wireless spectrum opportunistically.

IV. LONG SHORT TERM MEMORY

Long short-term memory (LSTM) is an artificial neural network used in the fields of artificial intelligence and deep learning. Unlike standard feed forward neural networks, LSTM has feedback connections. Such a recurrent neural network (RNN) can process not only single data points (such as images), but also entire sequences of data (such as speech or video). For example, LSTM is applicable to tasks such as unregimented, connected handwriting recognition, speech recognition, machine translation, robot control, video games, and healthcare. The name of LSTM refers to the analogy that a standard RNN has both "long-term memory" and "short-term memory". The connection weights and biases in the network change once per episode of training, analogous to how physiological changes in synaptic strengths store long-term memories; the activation patterns in the network change once per time-step, analogous to how the moment-to-moment change in electric firing patterns in the brain store short-term memories. The LSTM architecture aims to provide a short-term memory for RNN that can last thousands of time steps, thus "long short-term memory".

A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three *gates* regulate the flow of information into and out of the cell.

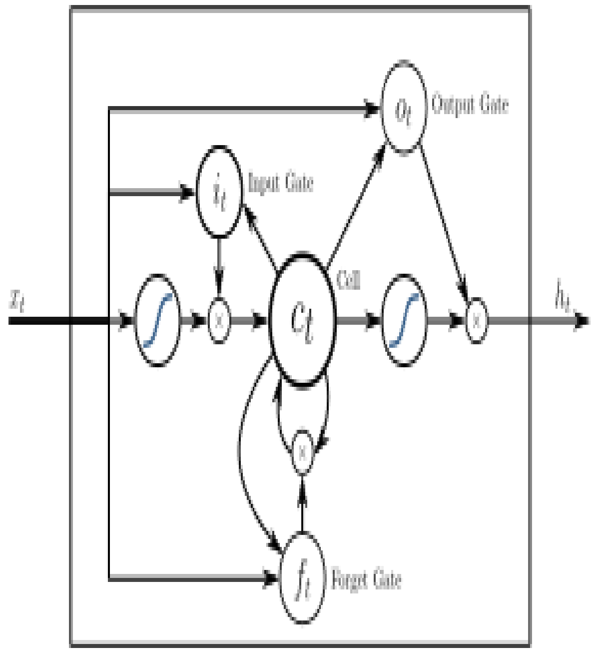


Figure 3: Long Short Term Memory

LSTM networks are to classify, processing and making predictions based on data, since there can be lags of unknown duration between important events in a time series. LSTMs were developed to deal with the vanishing gradient problem that can be encountered when training traditional RNNs. Relative insensitivity to gap length is an advantage of LSTM over RNNs, hidden Markov models and other sequence learning methods in numerous applications.

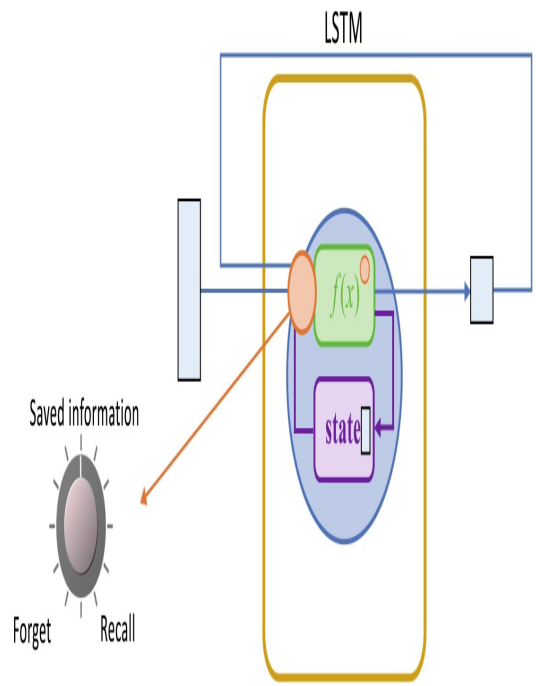
A. IDEA

In theory, classic RNNs can keep track of arbitrary long-term dependencies in the input sequences. The problem with vanilla RNNs is computational (or practical) in nature: when training a vanilla RNN using back-propagation, the long-term gradients which are back-propagated can "vanish" (that is, they can tend to zero) or "explode" (that is, they can tend to infinity), because of the computations involved in the process, which use finite-precision numbers. RNNs using LSTM units partially solve

The vanishing gradient problem, because LSTM units allow gradients to also flow unchanged. However, LSTM networks can still suffer from the exploding gradient problem.

In the equations below, the lowercase variables represent vectors. Matrices and contain, respectively, weights of the input and recurrent connections, where the subscript can either be the input gate, output gate, the forget gate or the memory cell, depending on the activation being calculated. In this section, we are thus using a "vector notation". So, for example, is not just one unit of one LSTM cell, but contains LSTM cell's units.

Figure 4: LSTM Input Gate



A sequence of repeating neural network modules makes up all recurrent neural networks. This repeating module in traditional RNNs will have a simple structure, such as a single tan layer.
The output of the current time step becomes the input for the following time step, which is referred to as Recurrent. At each element of the sequence, the model examines not just the current input, but also what it knows about the prior ones.

B. BIDIRECTIONAL LSTMS

Each training sequence is presented forwards and backwards to two independent recurrent nets, both of which are coupled to the same output layer in Bidirectional Recurrent Neural Networks (BRNN). This means that the BRNN has comprehensive, sequential knowledge about all points before and after each point in a given sequence. There's also no need to identify a (task-dependent) time window or goal delay size because the internet is free to use as much or as little of this context as it needs.

Conventional RNNs have the disadvantage of only being able to use the previous contexts. Bidirectional RNNs (BRNNs) do this by processing data in both ways with two hidden layers that feed-forward to the same output layer. When BRNN and LSTM are combined, you get a bidirectional LSTM that can access long-range context in both input directions.

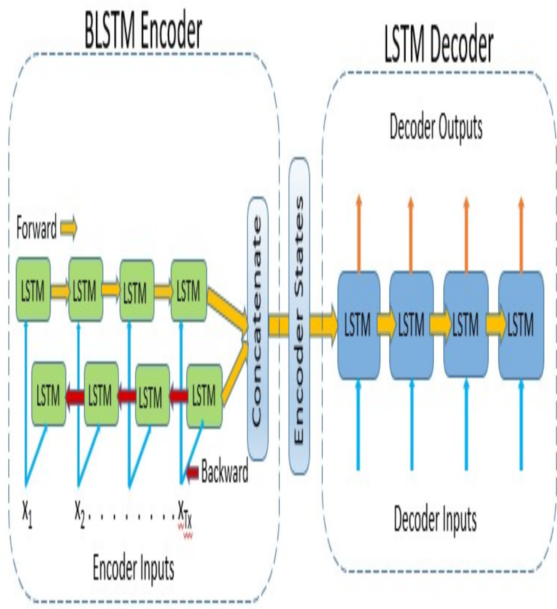


Figure 5: LSTM Encoder Decoder

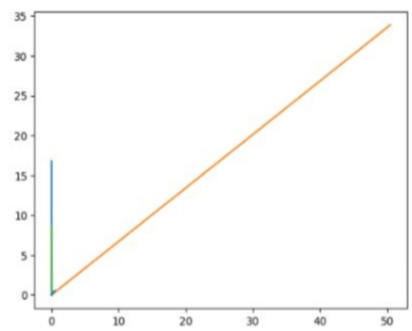
C. ANACONDA NAVIGATOR

Anaconda Navigator is a desktop graphical user interface (GUI) included in Anaconda distribution that allows users to launch applications and manage condo packages, environments and channels without using command-line commands. Navigator can search for packages on Anaconda Cloud or in a local Anaconda Repository, install them in an environment, run the packages and update them. It is available for Windows, macros and Linux.

The distribution includes data-science packages suitable for Windows, Linux, and macros. It is developed and maintained by Anaconda, in, which was founded by Peter Wang and Travis Oliphant in 2012. As an Anaconda, Inc. product also knows Anaconda Distribution or Anaconda Individual Edition, while other products from the company are Anaconda Team Edition and Anaconda Enterprise Edition, both of which are not free. Package versions in Anaconda are managed by the package management system condo. This package manager was spun out as a separate open-source package as it ended up being useful on its own and for things other than Python. There is also a small, bootstrap version Anaconda called Minion, which includes only condo, Python, the packages they depend on, and a small number of other packages.

V.RESULTS

The simulation results are presented here to demonstrate the proposed model's performance. The effect of parameters such as modulation schemes, sample length and, classification models is investigated. This section presents and compares the results of our model with other deep neural network models, namely convolutional neural network (CNN), Lent, residual network (Reset), inception, LSTM, convolutional long short-term deep neural network (CLDNN) and previously reported spectrum sensing models of Detect Net and CNN-LSTM . For a desirable model, we need to achieve a low probability of false alarm, between 0 to 0.1 according to the IEEE 802.2 2 standard, low sensing error, and high probability of detection.



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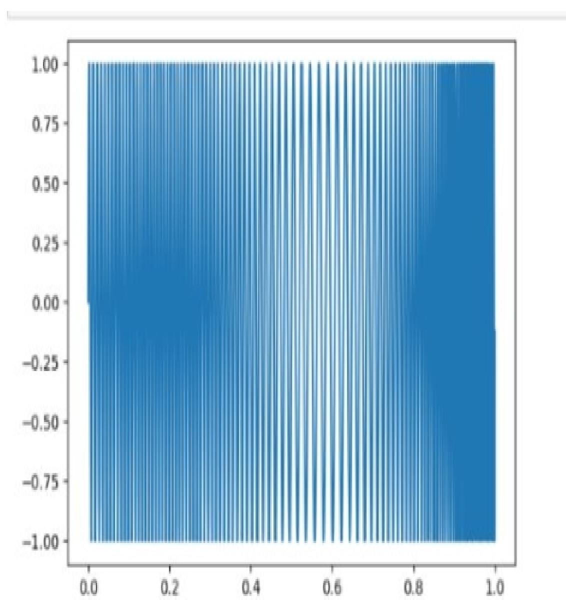
Y-Represents the Probability of detection

For demonstrating the proposed D Lessened model’s efficiency, the receiver operating characteristics (ROC) curves of the proposed model are compared with that of other models. It can be observed that the proposed model outperforms other models with an apparent margin. The CNN module of Dispense Net scrutinizes the patterns of the received signal. The extracted features are provided as input to the LSTM such that the temporal features of the input sequence can be learned. The graphical features are processed by CNN, but it is not designed for processing temporal characteristics. The inception architecture inspires the proposed model since it is capable of balancing generalization and complexity. Additionally, the inception architecture performs similarly to the proposed model in terms of probability of detection but performs poorly in case of false alarm.



Receiver operating characteristics (ROC) Curves.

VI. Conclusion

Cognitive radio technology as discussed in this project has proven to be a great boon for efficient spectrum utilization to fulfill the spectrum demand of growing wireless technologies. This project gives an overview of the system models that implement spectrum sensing algorithms, classification of spectrum sensing techniques and their comparison on the basis of test statistics, detection accuracy, complexity, robustness, sensing time, etc. It also provides a brief summary of research challenges associated with spectrum sensing, standards and hardware platforms that helps in real time implementation of spectrum sensing techniques. Basically, the main focus of this project is the study of narrowband spectrum sensing techniques like energy detection, feature detection, matched filter detection, etc. and their research challenges.

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