Performance Analysis of LSTM-CNN for Spectrum Sensing in Cognitive Radio Networks

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Abstract

Spectrum sensingis a primary task for Cognitive Radio Networks. Deep Learning Models have proven its efficiency in SS and currently lot of research is focused on implementing it in practical Scenarios. However, for practical implementation, it is necessary that spectrum sensing should be from assumptions that are made by deep learning models. CNN is a very powerful model for extracting spatial characteristics such as sample covariance matrix. On the other hand, LSTM uses predictive sensing by extracting time series data. For efficient Spectrum sensing -Deep learning model, this paper proposes LSTM-CNN model to extract temporal as well as spatial data from the incoming signal. According to simulation results, LSTM-CNN outperforms CNN and the LSTM method separately.To further prove efficiency of the model we have compared the result from ML techniques like SVM and LR also.

Keywords:CNN, LSTM, Spectrum sensing

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1. Introduction

We are witnessing the era of Internet of Things (IOT) where not only mobile devices are using internet but devices in smart homes, smart agriculture, smart e-commerce and smart city are also connected to the internet. This has resulted in enormous growth of devices and huge a mount of spectrum. However as per the study made by Federal Communications Commission (FCC) of the United States in 2003 [11,12] the spectrum is utilized only up to twenty percent. Cognitive Radio (CR) offers to utilizethe spectrum by unlicensed user called Secondary users (SU) without causing interreference from licensed user called Primary Users (PU). Opportunistic spectrum access is the need of the hour as we have to find out ways to handle the most valuable thing for communication i.e., Spectrum.

Cognitive Radio has four main functions (1) Spectrum Sensing (SS) (2) Spectrum Access (3) Spectrum Sharing and (4) SpectrumMobility [13]. Out of these Spectrum sensing is a primary task which identifies spectrum hole and then makes a decision about PU activity. There are lot of methods which has been utilized for SS which includes traditional methods like energy detection, Cyclostationary detection, matched filter detection etc. The SS task is also categorized into non-cooperative and cooperative decision model. Non-cooperative is a decision about PU activity based on single SU while cooperative SS employs many SU's to make the same decision. It is obvious that cooperative SS gives much better performance as compared to non-cooperative as the latter suffers from the impairments in the wireless channels as shadowing multipath fading, etc. This work describes a hybrid deep learning model based on CNN and LSTM named CNN-LSTMwhich is free from model assumptions. The remaining paper has been organized as follows: section 2 gives insight about literature review, section 3. Describes system model, section 4 discusses the methodology of LSTM-CNN based Spectrum sensing, section 5 discusses information about dataset and performance evaluation parameters and finally section 6 concludes the work described.

2. Literature Review

Machine learning models like Support Vector Machine (SVM), logistic regression (LR), Decision Tree (DT) etc have also shown better performance as compared to traditional methods [14]. Recently, Deep learning models have gained much popularity among researchers as it offers very powerful features for mobile and wireless network such as transfer learning, automatic feature extraction, no need of labelled data, multi-tasking learning etc. [15].There are many models which has been validated by researchers like Artificial Neural Network (ANN), Recurrent Neural Network

(RNN), Convolutional Neural Network (CNN),Long short-term memory (LSTM), Reinforcement Learning (RL) etc. Among these CNN and LSTM based models are most popular among researchers due to powerful extraction capability of special characteristics and later model has excellent extraction capability of temporal characteristics[16]. These models have a benefit that they are independent of model-based assumptions. Some of the main works include the Deep Transfer cooperative sensing (DTCS) method described in [20] makes use of energy vectors obtained from various SUs in a specific area in one radio frequency environment and transmits this information to another. TL improves detection capability while also significantly reducing the amount of training data. But this suffers from high computational complexity.STFT-CNN method described in [21]uses the signal samples' time-frequency domain information the results have been analyzed for randomly processed data. Also, this method is not able to handle large number of secondary nodes which is a primary requirement of cooperative spectrum sensing.

Summarizing issues faced by previous sensing techniques are as follows:

- Although LSTM-SS uses PU activity statistics to increase detection and classification accuracy, it takes much longer to train than other algorithms.[19]
- While the CNN-LSTM technique [18] is effective at tracing the signal's activity pattern, it suffers from high computational complexity and has room for development.
- CNNs are used in the APASS algorithm to learn both spatial and temporal properties, although they are ineffective at learning the temporal information of received signals.[17]

The two primary contributions of this work are (1) Suggest a spectrum sensing detector based on deep learning that is independent of model assumptions. When compared to conventional LSTM and CNN detectors, (2) increase accuracy and reduce computing complexity. The proposed method surpasses the conventional methods in terms of detection accuracy as well as shorter computing and sensing times, according to simulation findings.

3. System Model

Here we are considering a cooperative scenario with single PU and multiple SU’s. Assumption is made for centralized cooperative SS in which there is a fusion center as shown in figure 3.1. All the nodes pass their individual sensing decision to the fusion center and based on some rule i.e., AND, OR, K-out-of-N etc. rule final decision is made whether PU is present or absent.

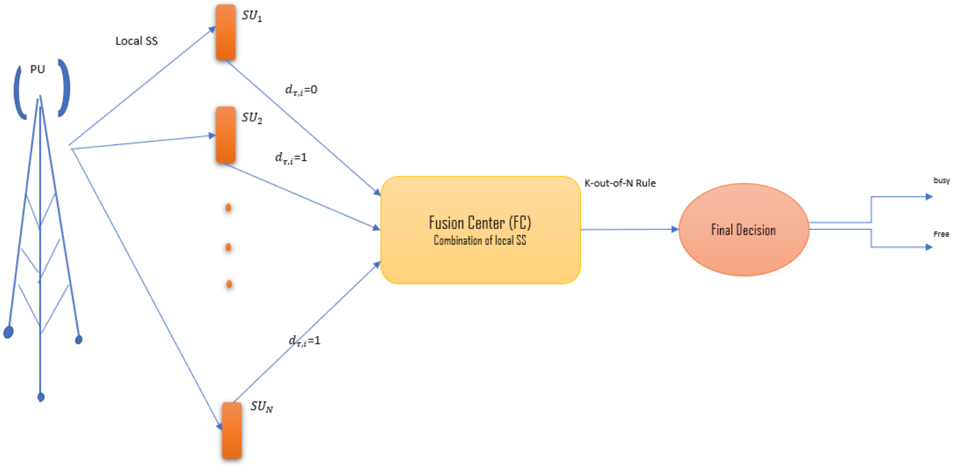

Fig 3.1 Centralized Cooperative spectrum sensing [2]

Figure 3.2 shows the slot structure of centralized cooperative detection. Here local sensing time and reporting time of all SU's are considered in total time slot. After decision making only effective transmission starts. [3]N samples are collected at the beginning of each frame or v-th sensing period, after which the SU can choose to broadcast or remain silent in order to shield the PU from interference for the remainder of the frame. The equation for received signal$y_v(n)$ is :

$$\mathscr{H}_0:\quad \{k_v(n)\}_{\mathrm{n}=1}^{N} = \{\varepsilon_v(n)\}_{\mathrm{n}=1}^{N}$$

$$\mathscr{H}_1:\quad \{k_v(n)\}_{\mathrm{n}=1}^{N} = \{h_v r_v(n)\}_{\mathrm{n}=1}^{N} + \{\varepsilon_v(n)\}_{\mathrm{n}=1}^{N} \qquad (3.1)$$

Where, $\mathcal{H}_0$ is hypothesis that PU is in silent state and alternate hypothesis states that PU is in active state. In the simulations, we assume that the noise $\varepsilon_v(n)$ on each antenna is complex Gaussian or complex Laplace distributed, and that the signal is QPSK modulated with unit energy. Since it is a frequent assumption in spectrum sensing that the channel coherence time is longer than the sensing period, the channel remains constant during the v -th sensing period. The received signal samples in v -th sensing period is given by $K_v(n) = [k_v(1), k_v(2) \ldots\ldots k_v(n)]$.

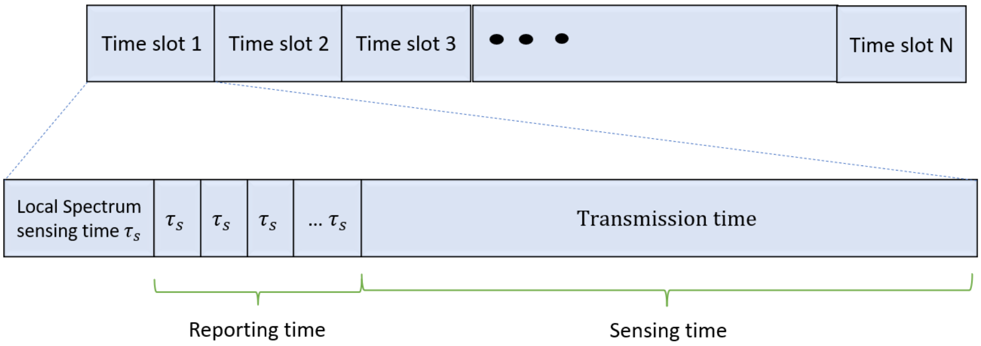

Fig3.2. Slot Structure in Cooperative Detection

4. LSTM-CNN based Spectrum Sensing

As shown in Figure 4.1, sample covariance matrix is taken as an input to the CNN. The CNN architecture consists of three convolution layers along with max pooling layers and one fully connected layer with SOFTMAX function for decision. ReLU is used as an activation function. The hyperparameters of three layers of convolution along with maxpooling layer are given in table 3.1.

Table 4.1: CNN hyper parameters

Convolution layer 1 16@(2×2)	Convolution layer 2 32@(5×5)
Max pooling layer 2×2	Max pooling layer 2×2
Dense Module 1024 neurons	

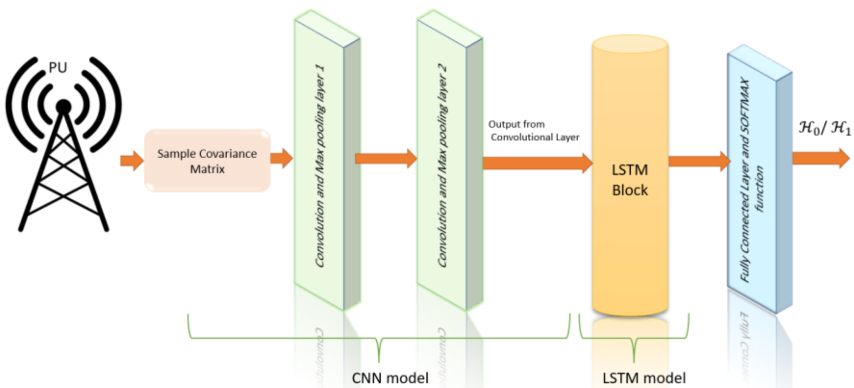

Figure 4.1. System model of LSTM-CNN

As shown in Figure 4.1, sample covariance matrix is the input to the LSTM-CNN model

$$C_v = \frac{1}{N} K_v {K_v}^z \tag{4.1}$$

So, the input dataset becomes $\{(c_1, l_1), \dots, (c_v, l_v), \dots .(C_v, L_v)\}$ we rearrange the data to introduce time sequence ∂ , so the dataset becomes $\aleph$= $\{(\aleph_1, l_\partial), \dots (\aleph_v, l_{v+\partial-1}), \dots (\aleph_{v-\partial+1}, L_v)\}$ where $\aleph_v = [C_v, C_{v+1}, \dots, C_{v+\partial-1}]$, these sample covariance matricesare in complex values so they can be seen as a 2D image. CNN modules extract special correlation while LSTM extracts temporal characteristics. The output of the CNN module is flattened as $\beth_t = Concatenate$ ($\beth_1$,$\beth_2$,)and then input is given to the LSTM cells. To change the output dimension based on the number of data classes, the output of LSTM cells that comprise energy feature, correlation, and temporal features is then fed to a fully connected layer [4].

Convolution Layer's, current output $\beth_\partial$ is used as an input to the LSTM block, whose actions are described in equation (4.2). Let$\emptyset_\partial$ and $\emptyset_{\partial-1}$be present and previous output of LSTM block. Also, current state be $F_t$and F_{t-1} be the previous state. Then operations of LSTM block will be given by:

$$\begin{aligned} \nabla_u &= \vartheta(\omega_u[\emptyset_{\partial-1}, \beth_\partial] + \rho_u) \\ \nabla_f &= \vartheta(\omega_f[\emptyset_{\partial-1}, \beth_\partial] + \rho_f) \\ \nabla_o &= \vartheta(\omega_o[\emptyset_{\partial-1}, \beth_\partial] + \rho_o) \end{aligned} \tag{4.2}$$

ϑ is the sigmoid function with operation $\vartheta = 1/1 + e^{-x}$,∇_u are the values of update, forget and output gate respectively.ρ_u,$\rho_f$and $\rho_o$are the biases of update, forget and output gate.ω are the weights. LSTM output $\emptyset_\partial$can be given by:

$$\begin{aligned} F_\partial &= \nabla_u \odot \tilde{F}_\partial + \nabla_f \odot F_{\partial-1} \\ \emptyset_\partial &= \nabla_o \odot \tanh(F_\partial) \end{aligned} \tag{4.3}$$

For the decision, Fully Connected (FC) layer receives this output from the LSTM, which consists of energy, eigenvalues, and temporal dynamics. According to the data classes, the output dimension is finally adjusted. For the Network's training, the loss function, which is categorical cross entropy, is provided by

$$Loss_\theta(\tilde{k}_v, k_v) = -\sum_q (k_v[q] log\tilde{k}_v + (1 - k_v[q]) log\tilde{k}_v[q]) \tag{4.4}$$

Here as in equation (9), $\tilde{k}_v$ is the predicted output while k_v is actual output. The loss function should be minimized. The parameters and hyperparameters, which were given random initial values, will be adjusted throughout the training procedure. The gradient is calculated using this loss, and the weights are updated using the gradient. In order to maintain regularity, the dropout ratio was set at 0.02. This lessens the chance of overfitting. The ADAM optimizer is used to improve the network parameters.

4. Performance Analysis

A. Dataset Generation

The dataset is a synthetic variable-SNR database generated by O'Shea and West [1] by GNU radio, which is a deep sig dataset named RADIOML 2016.10A. It consists of 11 modulation scheme (8 digital and 3 analog). This variable-SNR dataset can be used to assess performance under various situations of signal and noise power with mild LO drift, light fading, and varying labelled SNR increments [6].

B. Performance Evaluation

We have used three performance metrics to analyze the performance of the LSTM-CNN model.Firstly, the model is analyzed with probability of detection P_d, which is defined as detection PU's activity when PU is actually present. Secondly, the performance has been evaluated through probability of false alarm P_f which is defined as detecting PU's activity when PU is actually vacant. Thirdly, we have defined Sensing time (ST) as the total time of effective transmission as explained in figure 2.2 [5].

5. Results and Discussion

Performance analysis of LSTM-CNN model has been done assuming Rician channel. Results confirm the effectiveness of the model. In this section, the performance of our model is compared to that of various Deep Learning models, including the Convolutional Neural Network (CNN) and the Long-Short Term Memory (LSTM) model. Support Vector Machine (SVM) and Logistic Regression (LR) models from Machine Learning are also included in the comparison.

To demonstrate the detection capability of LSTM-CNN comparison is made with SVM, LR, CNN and LSTM models. When signal to noise ratio is set to -20dB then the detection performance of 0.16253is seenfor LSTM-CNN while at SNR=-5dB then the performance of 0.961456. The proposed method has significant detection performance improvement not only over SVM and LR but also, with CNN and LSTM model when applied separately. From figure 5.1 it is clear that at very low SNR's also the performance is far better than its competitor's performance.

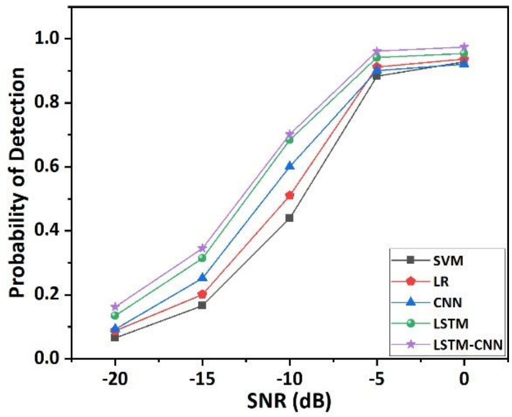

Figure 5.1Performance Comparison of detection performance of LSTM -CNNwith SVM, RF, CNN and LSTM

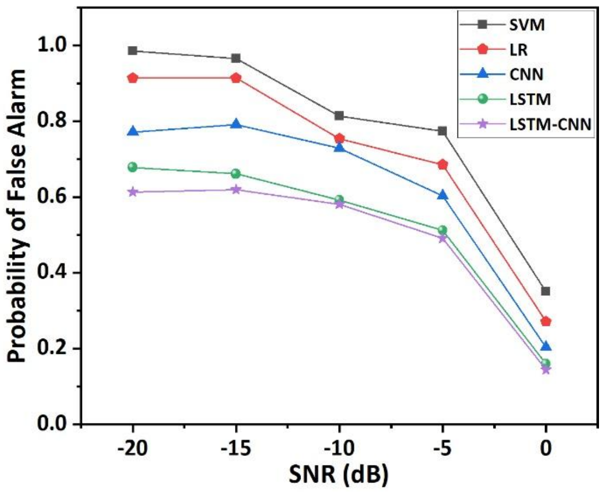

Figure 5.2 Performance Comparison of False Alarm performance of LSTM -CNNwith SVM, RF, CNN and LSTM

Figure 5.2 shows the comparison of probability of false alarm (PF) of LSTM-CNN with SVM, LR, CNN and LSTM models. As shown in table 5.1 the probability of false alarm at SNR=-20dB is 0.61345while the probability at SNR=-5dB is 0.491256. A low probability of false alarm (PF), between 0 and 0.1, is required by the IEEE 802.22 standard for a desired model.[17]. From figure 5.2 and table 5.1 it is clear that significance performance improvement is seen for LSTM model.

Table 5.1: Performance comparison metrics of LSTM-CNN for Rician Channel

	SNR	SVM	LR	CNN	LSTM	LSTM-CNN
Probability of Detection	-20dB	0.065126	0.087451	0.092143	0.134654	0.16253
	-5dB	0.884126	0.912377	0.901426	0.941477	0.961456
Probability of False Alarm	-20dB	0.985413	0.914258	0.772057	0.678451	0.61345
	-5dB	0.7737	0.685413	0.603423	0.512469	0.491256
Sensing Time (ms)	-20dB	331.2587	322.8745	318.8745	311.87451	309.854
	-5dB	321.8745	315.1426	309.8542	302.74513	300.12578

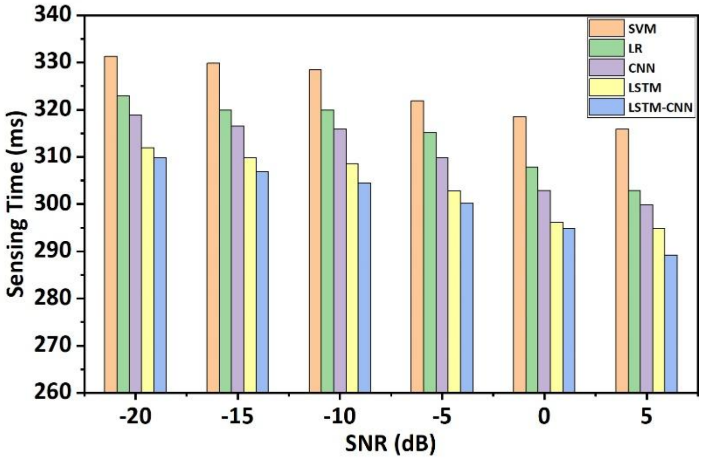

Figure 5.3 Comparison of sensing time of LSTM integrated AlexNet

Sensing time is the total effective transmission from the SU nodes. Every deep learning and machine learning model aims to speed up detection and decrease sensing time. Here sensing time (ST) is compared to SVM, LR, LSTM and CNN. ST at SNR=-20dB, for SVM is 331.2587ms, LR is 322.8745ms, CNN is 318.8745ms, LSTM is 311.87451ms and LSTM-CNN is 309.854ms Sensing time for LSTM-CNN is noticeably reduced. This demonstrates its superior sensing capacity to other models.

Our suggested work takes advantage of the CNN Architecture for extracting spacial features as well as the LSTM model's outstanding temporal characteristic extraction. The outcomes demonstrate that LSTM-CNN outperforms currently efficient Deep Learning and Machine Learning models. The enhanced performance suggests a more accurate identification of PU transmission over the spectrum.

VII. Conclusion

This article describes performance of LSTM-CNN Deep Learning model for Spectrum sensing in cognitive radio networks. Here, Cooperative SS is considered with Single-input-multiple-output (SIMO) environment. The output of CNN model is fed to the LSTM model, so the detection performance leverages the benefits of both models. Simulation results show that the model outperforms CNN and LSTM model when applied separately in terms of detection capability as well as sensing time. Also, the results have been compared with Machine Learning models like SVM and LR for showing significant performance improvement.

Declaration

The authors affirm that they have no known financial or personal conflicts of interest that would have an impact on their work on this research.

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