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Deep Learning-Based Spectrum Sensing in Cognitive Radio Networks using Stacked LSTM: Performance Analysis of SNR and BER

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Abstract: Rapid evolution of wireless communication technologies and emergence of 5G networks have addressed lack of spectrum resources, highlighting the need for innovative topologies to improve the spectrum utilization. Due to this reason, Cognitive Radio (CR) has evolved as an optimized solution to overcome these difficulties by allowing dynamic spectrum access, thereby reducing the under-usage of available spectrum. Considering this, precise and accurate spectrum sensing is essential for CR to identify unused spectrum and ensure minimal interference with licensed users. This paper introduces novel Stacked Long Short-Term Memory (LSTM) network-based spectrum sensing algorithm for achieving enhanced sensing accuracy in Cognitive Radio Networks (CRNs). Stacked LSTM model is developed to capture temporal dependencies in incoming signals, facilitating robust spectrum sensing even under dynamic environments. The effectiveness of the stacked LSTM model is determined using key metrics such as Signal-to-Noise Ratio (SNR) and Bit Error Rate (BER). To validate its adaptability across various noise situations, this model is trained on a diverse set of signals with differing SNR levels. Simulation results indicate that Stacked LSTM significantly improves spectrum sensing accuracy, specifically in low-SNR conditions, when compared to conventional energy detection approaches. In addition to this, BER analysis depicts that the proposed model attains high transmission reliability, even under difficult and challenging channel situations, by efficiently reducing the BER.

Keywords: Wireless communication technologies, Cognitive Radio (CR), stacked LSTM, SNR, BER.

Introduction

The exponential growth in wireless communication demand necessitates efficient spectrum utilization across increasingly complex network architectures (Kim et al., 2021). The proliferation of 5G systems and beyond has intensified spectrum scarcity challenges, creating critical bottlenecks in network capacity and service quality (Liu et al., 2022). Cognitive Radio (CR) technology has emerged as a promising solution, enabling dynamic and opportunistic spectrum access while protecting licensed Primary User (PU) transmissions from interference (Sairam et al., 2024).

CR systems possess the capability to adaptively reconfigure transmission parameters through intelligent interaction with the surrounding radio environment (Tekbıyık et al., 2021; Abdalzaher et al., 2021). Unlike conventional fixed-parameter radio systems, CR combines cognitive capability, the ability to sense, learn, and reason about environmental conditions, with reconfigurability, enabling dynamic adjustment of operational parameters including frequency, modulation, and power (Hossain et al., 2021). These cognitive capabilities enable Secondary Users (SUs) to identify and exploit spectrum opportunities without degrading PU communications (Varun et al., 2022; Arivudainambi et al., 2022).

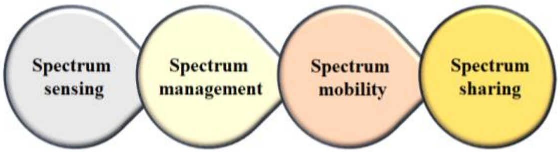

Fig. 1. Key functions of CR

CR functionalities encompass radio environment analysis, dynamic spectrum management, channel state estimation, and adaptive power control, collectively enabling coexistence between PUs and SUs while maximizing spectrum efficiency (Chauhan et al., 2021; Mohanakurup et al., 2022). However, wireless propagation phenomena, including multipath fading, shadowing, and hidden terminal problems, significantly degrade spectrum sensing performance. Machine Learning (ML) and Deep Learning (DL) approaches have emerged as promising solutions for mitigating these sensing challenges and improving channel characterization accuracy (Obite et al., 2021).

Early ML-based spectrum sensing employed classifiers including Gaussian Mixture Models (GMM), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) to classify energy vectors and reduce false alarm rates in Cognitive Radio Sensor Networks (CRSN) (Venkatapathi et al., 2024). While these approaches improved detection accuracy and spectrum utilization, they suffer from substantial training computational requirements, noise sensitivity, and limited real-time applicability. Abusubaih et al. (2021) proposed K-means clustering for robust performance under high-noise conditions, though this method requires extensive training samples and numerous cooperating SUs to achieve acceptable performance.

DL architectures offer advantages over conventional ML through automated feature extraction, eliminating manual feature engineering requirements. Convolutional Neural Networks (CNNs) have demonstrated efficacy in spectrum sensing by processing spectrogram representations for PU signal detection (El-Shafai et al., 2022). However, CNN-based approaches impose significant computational overhead and demand substantial training data volumes. Deep Neural Networks (DNNs) have been applied to multi-user CR scenarios, distinguishing active from inactive PUs using composite detector statistics (Nasser et al., 2021), though DNNs similarly require extensive training datasets and computational resources.

Hybrid architectures combining CNNs with Transfer Networks (TN) have been proposed for feature extraction and spectrum selection (Vijay et al., 2024), while CNN-LSTM models incorporating multi-head self-attention mechanisms have improved collaborative sensing accuracy (Wang et al., 2025). Despite these advances, existing DL-based spectrum sensing methods face persistent limitations including high computational complexity, data dependency, overfitting susceptibility, environmental sensitivity, communication overhead in cooperative sensing, scalability constraints, and synchronization requirements (Saraswathi et al., 2024; Liu et al., 2021).

Research Contribution

This paper proposes a stacked Long Short-Term Memory (LSTM) architecture for spectrum sensing in CR networks, addressing the temporal dependency modeling limitations of existing approaches. The primary contributions are:

- Enhanced Temporal Modeling: A stacked LSTM architecture that effectively captures long-term temporal dependencies in spectrum occupancy patterns, improving detection accuracy under dynamic spectrum conditions.
- Improved Robustness: Enhanced performance stability across varying environmental conditions through recurrent architecture inherently suited to sequential signal processing.
- Real-Time Adaptability: Superior generalization to diverse and noisy operational environments, enabling reliable spectrum sensing under practical deployment conditions with reduced training data requirements compared to conventional DL approaches.

The proposed methodology advances CR spectrum sensing by leveraging LSTM's sequential modeling capabilities while mitigating computational complexity and data dependency constraints characteristic of existing DL architectures.

Methodology

Figure 2 illustrates the proposed CR system process flow for effective spectrum sensing. Initially, the process begins with signal pre-processing, during which the original input signals are filtered and rectified to remove noises and unwanted interference, thereby, assuring high quality signals. After signal pre-processing state, the processed signals are fed into stacked LSTM network. The stacked LSTM contains multiple layers which process the signals more effectively by enabling to handle complex signals making an efficient DL based model for enhanced spectrum sensing process.

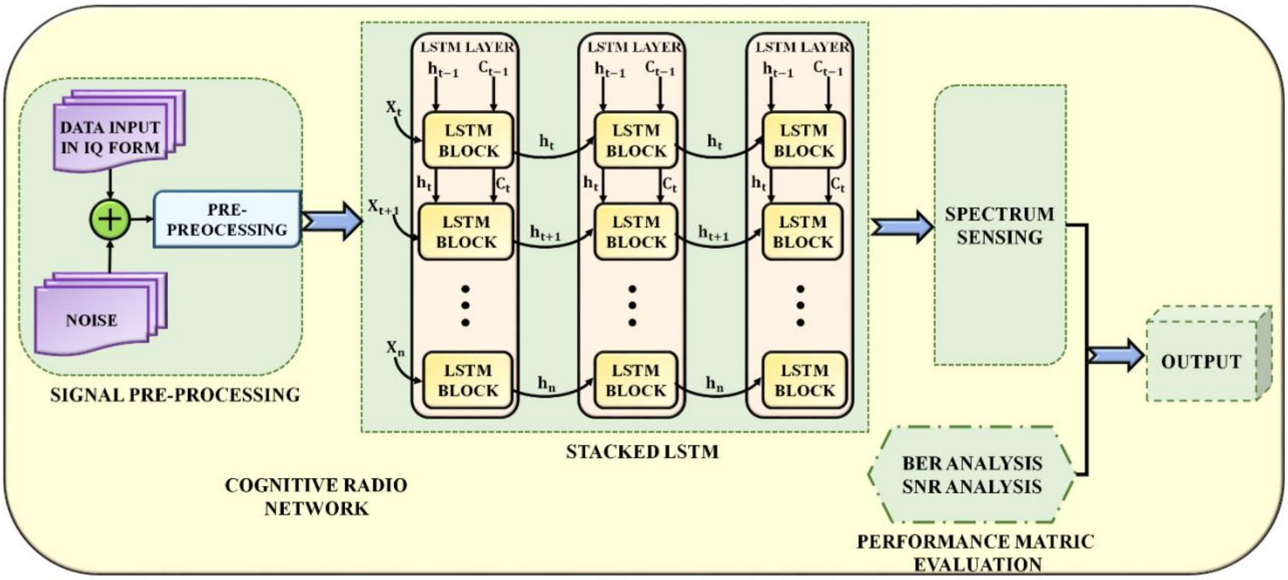

Fig. 2. Proposed system process flow

The outputs obtained from stacked LSTM are then fed to the spectrum sensing block, where the frequency of the spectrum is analysed to determine available spectrum. Finally, effectiveness of spectrum sensing is calculated using metrics such as BER and SNR, which allows for the identification of the system efficiency. Later, the evaluated results are given to the output block. Therefore, the proposed system using DL based spectrum sensing demonstrates that the integration of DL approaches provides enhanced and effective spectrum performance, thus improving the wireless communication network efficiency.

Modelling of CRN

The CRN structure consists of two networks, namely primary network and secondary network, where primary network involves licensed users in which primary user possess access to this particular network. Whereas, secondary network does not contain any licensed users but it is has the ability to access the licensed network without disturbing the primary user. Figures 3 illustrates the basic structure of a CR, showing SUs dynamically discovering and accessing unused spectrum when there is no interference with the licensed PU.

Here, α represents the power gain of the interference connection between PU_{Tx} and SU_{Tx}, and β represents power gain of communication link between SU_{Tx} and SU_{Rx}. Because $\mathrm{SU}_{Rx}$is farther away from PU_Tx, it does not produce interference with PU_{Tx}. This refers to the individual user. Communication between SUs gets challenging when there are many of them, which is connected to spectrum access.

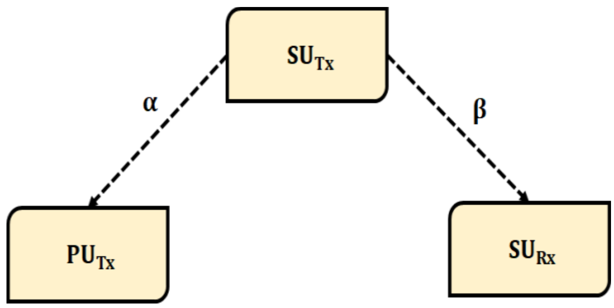

Fig. 3. Basic CR structure

In contrast, in a multi-user network, all the present users are obligated to share the common resources efficiently and Figure 4 depicts a multi-user scenario that lets several SUs access an identical frequency band. Spectrum sharing rules manage this relationship and perform an important role in establishing the best spectrum sensing technique.

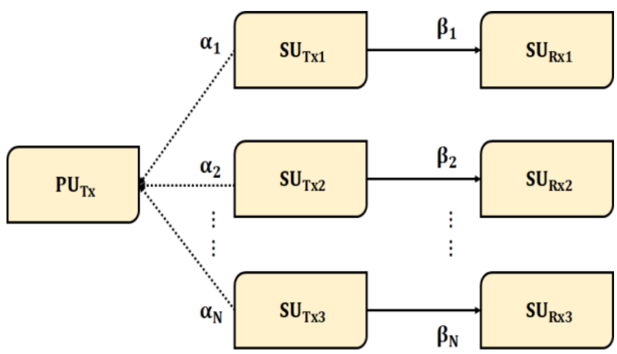

Fig. 4. Multi-user Network

Where, $\propto_1$, $\propto_2$ and $\propto_3$ represent channel power gain interference link, β_1, β_2 and β_3 refer to transmission links. As multiple users share that particular frequency band with PU_{Tx} , spectrum sharing is further divided into two types namely varying spectrum sensing and cooperative spectrum sensing. The limitations associated with dynamic spectrum sensing are interfering between PU → SU and SU. Figure 5 depicts the organization of the cooperative spectrum sensing system, in which various SUs share sensing findings via a Spectrum Coordinator (SC) and Fusion Center (FC).

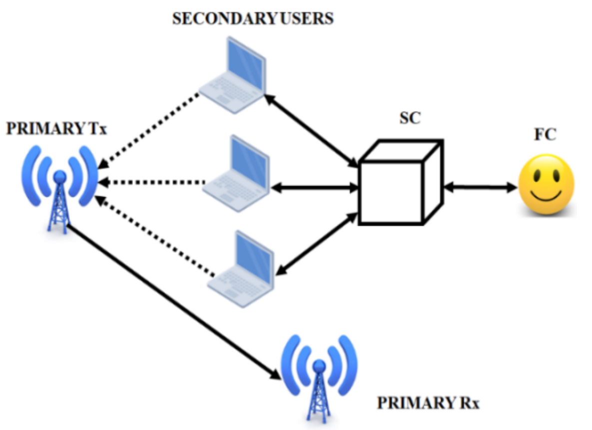

Fig. 5. Co-operative spectrum sensing

Each SU is dependent of spectrum sensing and determining available spectrum spaces. Later, SC gathers all the depicted information from SU and manages sensing events. Then SC directs sensing outputs to the FC and performs predicting primary user entry in channel. Finally, the results obtained are sent to SC, and the final results attained is shared between multiple users. To further enhance the spectrum sensing process DL-based stacked LSTM approach is utilized for achieving improved detection accuracy.

Modelling of Stacked LSTM

Spectrum sensing comprises certain challenges, including parameters such as effective spectrum utilization in Cognitive Radio Networks (CRN). Furthermore, since the data is time-dependent, it is crucial to evaluate the influence of previous spectrum usage on current allocation. To address these temporal dependencies, a LSTM network is deployed, which effectively captures long-term patterns in the spectrum sensing process. The LSTM architecture enhances adaptability to dynamic spectrum conditions, thereby improving robustness and prediction accuracy.

The LSTM network consists of three primary gates forget, input, and output that regulate flow of information. It utilizes the current input, previous hidden state, and previous cell state to generate the present output, which is then propagated to subsequent iterations. Specifically, the candidate cell state is computed using the hyperbolic tangent activation function as shown in Equation (1). The input gate (Equation (2)) and forget gate (Equation (3)) determine how much new information is added and how much past information is retained, respectively. The updated cell state is derived by combining these components (Equation (4)). Output gate (Equation (5)) controls exposure of the cell state, and final hidden state is computed as shown in Equation (6),

$$\widetilde{C_t} = \tan h\,(\,W_c\,[\,H_{t-1}\,, X_t] + \,b_c) \tag{1}$$

$$i_t \,=\, \sigma\,(\,W_i\,\,[\,H_{t-1}, X_t] + \,b_i\,) \tag{2}$$

$$f_t \,=\, \sigma\,(\,W_f[\,H_{t-1},\,X_t] + \,b_f\,) \tag{3}$$

$$C_t \,=\, f_t \circ C_{t-1} + \,i_t \circ \widetilde{C_t} \tag{4}$$

$$o_t \,=\, \sigma\,(W_o\,[\,H_{t-1},\,X_t] + \,b_0 \tag{5}$$

$$H_t \,=\, o_t \circ \tan\,h\,\,(C_t) \tag{6}$$

Here, C_t refers to the candidate vector, σ represents the sigmoid activation function, W_f , W_i and W_o indicate the gate weight matrix, b_f, b_c , b_i and b_0 imply the bias, i_t, f_t and o_t refer to the information flow control over the memory state C_t. Figure 6 presents the design of a stacked LSTM-based spectrum sensing model for CRN, with the use of stacked LSTM layers to extract complex temporal characteristics leading up to the accurate estimation of spectrum availability.

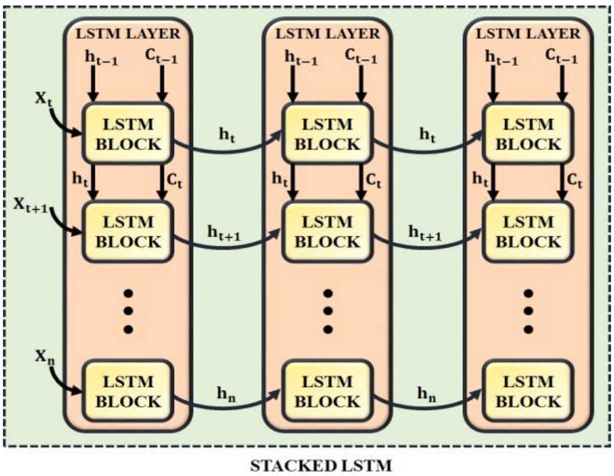

Fig. 6. Architecture of stacked LSTM

Weight initialization:

Using a uniform distribution method of sampling, the weights W are initialized in Equation (7),

$$W = u(-\sqrt{\frac{6}{n_{in}+n_{out}}}\sqrt{\frac{6}{n_{in}+n_{out}}}) \tag{7}$$

Here n_{in} and n_{out} denote input and output units of the layer. This initialization maintains variance stability across layers, which is crucial in deep systems like as stacked LSTM.

Activation Function:

The most prevalent activation functions seen in LSTM cells are sigmoid and $tanh$ the respective Equation (8) and Equation (9)

$$\text{Sigmoid: } \sigma(x) = \frac{1}{1-e^{-x}} \tag{8}$$

$$\text{Tan h: } \tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{9}$$

Whereas, stacking of LSTM enables to create a hierarchical feature representations from the input which is regarded as an essential aspect for accurate prediction even during complex and varying environments in CRN. A stacked LSTM is a DL based network, which improves the efficiency of training accuracy by increasing the depth of the network. In several fields such as time-series forecasting, fault diagnosis and signal detection, stacked LSTM provides more effective analysis than the traditional approaches. The depth of the network enables increased robustness for accurate predicting of spectrum availability and detecting unused frequency bands. As spectrum sensing includes evaluation of time-series data, increasing the number of layers in LSTM enables enhanced extraction of features. Thus, Stacked LSTM network consisting of multiple LSTM layers, in which the sequential output of each layer is given as the input to next.

The stacked model employed three LSTM layers with 128 neurons in each layer to learn complex representations of the signals and time dependence of the approach. The approach used an activation function of $tanh$ so that it learn the nonlinear relationship present in the data. The model trained for 140 epochs to accomplish the binary classification of spectrum availability with a batch size of 64 samples, and for this task a binary cross-entropy loss function used. A dropout rate of 0.2 also used as a constraint to help reduce over fitting and improve generalization to the model. All parameters are adjustable in order to achieve steady learning and improve classification accuracy for the specified SNR levels. The model trained by default Adam optimizer, primarily for its adaptive learning rate properties and efficient convergence and binary cross-entropy loss function summarized training classification error.

To extract features more efficiently, LSTM layers in network are stacked, thus resulting in a more reliable system with increased representational power. Significantly, a stacked-LSTM network is composed of three layers in which the first LSTM layer is responsible for extracting temporal features and resulting features are then fed to other layers for prediction. Therefore, this structure assures accurate prediction of spectrum availability, contributing to more effective spectrum management in CRN.

Training Dataset:

The dataset used real-world high SNR radio signals that had been collected using a USRP B210 SDR with GNURADIO. The dataset contains radio signals using different modulation types, collected in controlled conditions inside, and collected at two different distances (1 m and 6 m) with average SNRs of 37 dB and 22 dB, respectively. Each signal collected was split into 128 sample I/Q vectors and normalized. Sufficient variability in the dataset achieved through the number and variety of original signals collected. The proposed algorithm developed and implemented with Keras library with the Tensor Flow backend for training and testing the model. Dataset split into two SNR ranges; high SNR (−5 dB to +5 dB) and low SNR (−5 dB to −20 dB). There 7,00,102 samples available for training or testing. In order to find performance of proposed model, 70% of dataset used for training. Data is presented to the network in batches. Prediction accuracy, precision, recall, F1-score, probability of detection (P_d), and probability of false alarm (P_f), the metrics used to evaluate model performance. All training and assessment completed with Python and GNURADIO on common grade computing hardware with GPU compatibility.

Results and Discussion

The proposed system is implemented by the software includes GNURADIO and Python to determine performance efficacy in terms of improved calculation accuracy and spectrum sensing ability. The analyzers developed using Python collect high SNR signals. These data are then examined to identify PU signals. The analytical results are used in offline modes to validate the proposed spectrum sensing techniques. The obtained results are discussed along with their comparative analysis in this section.

Figure 7 represents the comparison of spectrum exhibited by signal and the interference produced by the signal at dB. Here, the interference signal overlaps to the useful information, appearing like low-power noise in the spectrum. There are traditional sensing methods where noise is hard to detect and make quantifiable due to the noise getting muddled up in the signal's spectrum. The stack LSTM model appropriately recognizes conditions based on an understanding of signal patterns through their temporal characteristics, which identifies useful spectra in these adverse conditions.

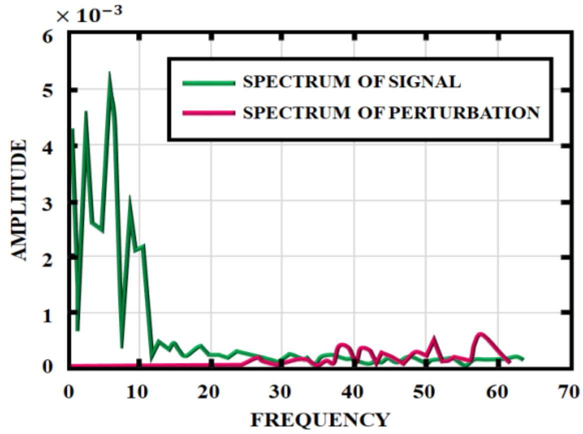

Fig. 7. Spectrum of signal and Perturbation

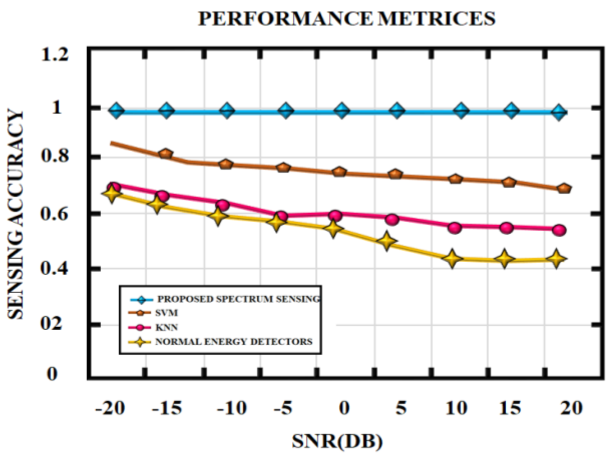

Fig. 8. Spectrum Sensing Accuracy

Figure 8 shows the spectrum sensing accuracy of various DL based approaches for different SNR (dB). The result depicts that for various conditions the proposed model accuracy remains stable throughout the process. The results show that other models drop in performance under low SNR conditions when the proposed stacked LSTM maintains high and stable accuracy. This illustrates that the proposed approach is robust, and capable to simplify very well across varying noise levels, which is an important consideration for real-world dynamic spectrum environments that constantly change SNR conditions.

Accuracy of signal prediction between actual and expected probabilities is shown in Figure 9. Probability of detection which is above 0.90, indicating high probability of prediction accuracy, thereby, increasing the reliability of the proposed model in detecting with a reduced false-negative rate. The increase in detection rate means minimal interference incurred with the license u ser from the perspective of CRN. This is vital for safe and effective spectrum access within CRN for shared or opportunistic spectrum access.

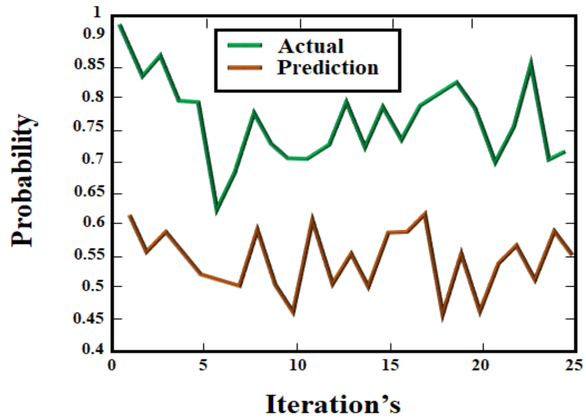

Fig. 9. Probability of detection

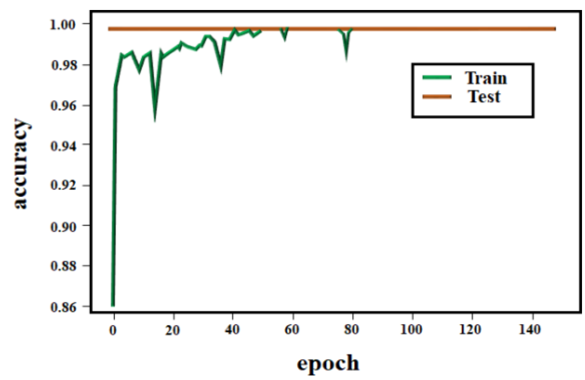

Fig. 10. Prediction Accuracy

Figure 10 shows Prediction accuracy of the proposed model using stacked LSTM approach during the training and testing process. In which the training periods depicts slightly fluctuated accuracy, whereas, testing accuracy remains smooth and consistent through the entire process, ensuring highly efficient model performance with higher predicting accuracy of 0.99. The model proved to be consistent by being highly stable, which indicates strong generalizing performance for real-time scenarios in CRN applications. Especially in non-deterministic environments unseen signal patterns occur, the proposed model conventionalize prediction performance responsively.

Figure 11 showcases the model loss graph for training and testing process. The depicted results showcase that, proposed stacked LSTM network enhances the spectrum sensing process in CRN with improved accuracy and efficiency with highly reduced losses. The minimal difference between the training and testing loss proves that the model is neither overfitting nor simply memorizing the training data and it assures consistent performance able to learn useful patterns.

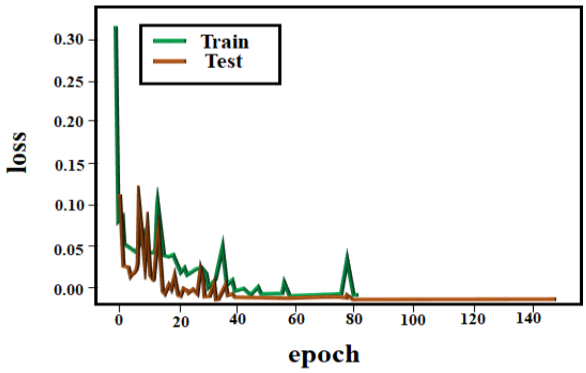

Fig. 11. Loss

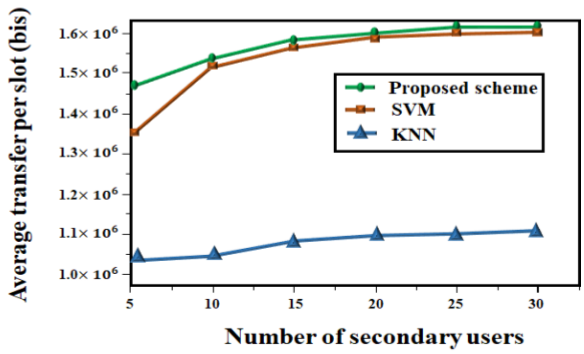

Fig. 12. Average transmission per slot

Figure 12 implies the average transfer per slot against number of secondary users, in which x-axis represents number of SU and y-axis represents average transmission rate. The proposed stacked LSTM model achieves the highest average transmission rate compared to other models. This proves that stacked LSTM model is better at both finding and using free spectrum. This information allows faster communication throughput and allows more users to be supported without creating more interference.

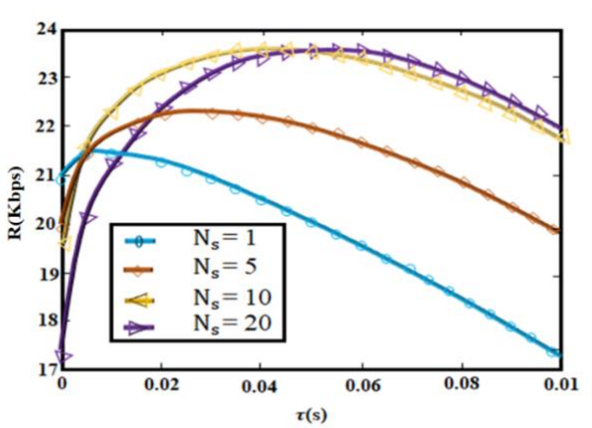

Fig. 13. Throughtput vs sensing time

Figure 13 indicates the throughput exhibited for different sensing time τ, where, $\mathrm{N_s} = 1$, $\mathrm{N_s} = 5$, $\mathrm{N_s} = 10$ and $\mathrm{N_s} = 20$, here $\mathrm{N_s}$ denotes number of sensing nodes. When time increases from 0 to 1 seconds, the throughput rapidly increases and further decreases and here, the curve $\mathrm{N_s} = 20$ attains the highest value of throughput, subsequently, $\mathrm{N_s} = 10$, $\mathrm{N_s} = 5$ and $\mathrm{N_s} = 1$.

When τ is small, high false alarm probability decreases spectrum access times of CR and when τ is large, long spectrum sensing time reduces useful communication time. Thus, either small or large τ values reduce CR's throughput. An optimal τ is found to maximize the throughput.

As demonstrated in figure, the throughput rises with sensing time (up to a second), and then decreases. This behavior stems from the sensitivity time/transmission time trade-off. When the sensitivity time is very short, there are a lot of false alarms, which decreases spectrum utilization. Somewhere in the mix of sensitivity time, the sensitivity time becomes too long, thereby taking time away from the available second's worth of transmission time, and thus overall throughput decreases. The optimal point (~1 sec) is one that properly balances detection accuracy and available transmission time. Past this point, any further sensing time only contributes marginally more in accuracy and decreases the communication time window.

Table 1. Performance metrics of the proposed network under various compositions

Composition	Low SNR Composition	High SNR composition
10:90	10	90
30:70	30	70
50:50	50	50
70:30	70	30
90:10	90	10

Table. 1 illustrates performance of proposed stacked LSTM, across varying SNR frequencies, specifically from low-SNR dominant scenarios (90:10) to high-SNR dominant (10:90). The detection performances are used to estimate the robustness and adaptability of model in varying SNR environment. The results indicate high detection accuracy with the stacked LSTM under low-SNR dominant environments demonstrating its capacity to be utilized in noisy, and dynamic spectrum conditions. As the proportion of low-SNR signals increases, the stacked LSTM continues to extract temporality from the signals, predicting spectrum availability. This authorizes that the stacked LSTM architecture is resilient across a spectrum of spectrum-sensing conditions, and used in realistic CRNs wherever signal quality and changes are all over the place.

Table 2. Comparison of performance metrics

Metric	LSTM-ELM [10]	CNN-LSTM [18]	Stacked LSTM
Computation Time	190ms	155.83ms	55ms
Convergence Speed	Slow	Medium	Fast
Total Epochs	250	100	140
Model Complexity	high	high	low
Optimizer	Adam	Adam	Adam
Loss Function	MSE	Cross-Entropy	Binary Cross-Entropy
Batch Size	30	32	64
Learning Rate	0.001	0.001	0.001

Table.2 presents a comparative analysis of three DL-based spectrum sensing models: LSTM-ELM [10], CNN-LSTM [18], and the proposed Stacked LSTM. Key performance metrics such as computation time, convergence speed (total number of training epochs), computational complexity, total model complexity, and other configurable inputs are measured. The Stacked LSTM model has the lowest computation time (55 ms), as well as the fastest convergence rate based on its comparatively low complexity and a higher batch size than the other models. All models used Adam optimizers, with the same learning rate (0.001), but they differ in the loss functions and other training configurations. The results clearly show that the stacked LSTM showed improved sensing performance based on complexity and speed of the model.

Figure 14 represents the prediction accuracy comparison between proposed stacked LSTM network and other conventional DL based networks such as CNN-SCF [4], ELM [7], Bi-LSTM [14] and LSTM-ELM [10]. From the above chart it is visible that, proposed DL based stacked LSTM network attained higher prediction accuracy of 0.99, indicating improved spectrum sensing ability in CRN. Among the classical models, LSTM-ELM and ELM had accuracies of 0.98, followed by CNN-SCF and Bi-LSTM with lower accuracies of 0.94 and 0.95. This comparison is a clear demonstration of the relative advantage of proposed architecture with respect to prediction accuracy, thereby validating its effectiveness for the given task.

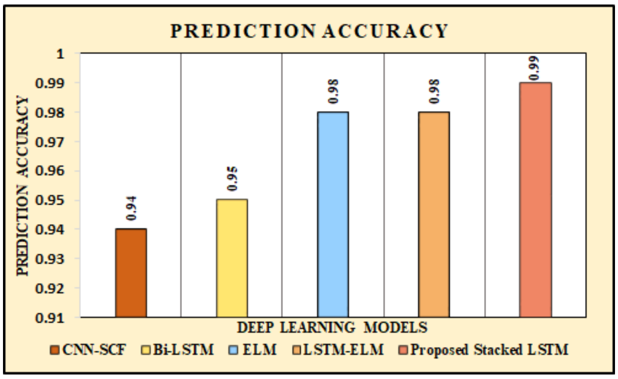

Fig. 14. Prediction Accuracy

The difference in performance between the stacked LSTM and Bi-LSTM models are due to the model structures. The Bi-LSTM accounts for temporal dependencies in both directions, but the stacked LSTM has greater network depth, it is able to model more complex temporal trends. Specifically, in CRN, where there is a sequential representation of signal patterns, and future data won't be available immediately, a unidirectional stacked LSTM avoids unnecessary computation of a backward pass, adheres to the principles of causal inference, and is therefore more practical to deploy.

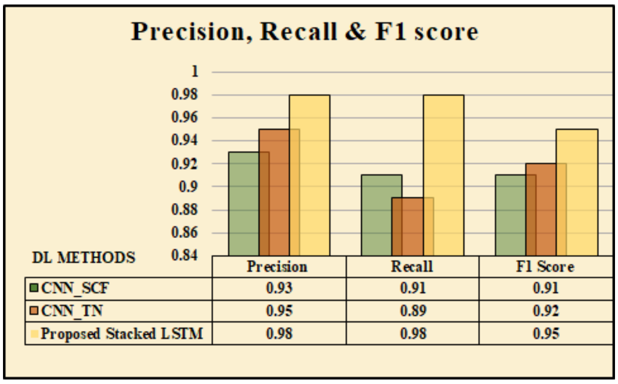

Fig. 15. Precision, Recall and F1 Score comparison

Figure 15 indicates performance metrics attained by proposed stacked LSTM network and other conventional DL based approaches. The CNN-TN [17] model achieved a values of 0.95 for precision, 0.89 for recall, and 0.92 for F1-score. Similarly, CNN-SCF [4] had 0.93, 0.91, and

0.91 respectively. In all the three aspects proposed approach scored higher value of precision (0.98), recall (0.98) and F1-score (0.95) when compared other approaches, ensuring highly efficient spectrum sensing in CRN, thus superior classification capabilities and enhanced usage of available spectrum.

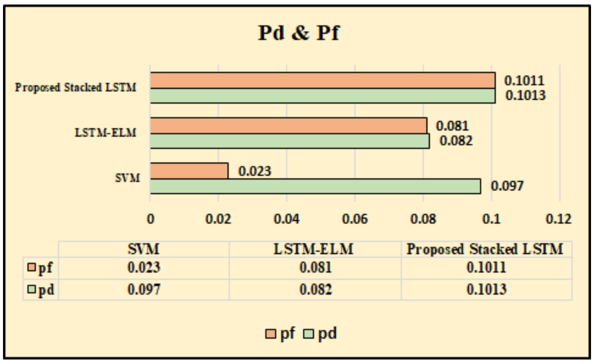

Fig. 16. Comparison of P_d and P_f

Figure 16 show a comparison of probability detection P_d and false alarm P_f for SVM [12], LSTM-ELM [10], and the Proposed Stacked LSTM model. The Proposed Stacked LSTM achieves the highest detection rate with P_d of 0.1013 and retains a low false alarm rate of P_f of 0.101, outperforming LSTM-ELM P_d of 0.082, P_f of 0.081 and SVM P_d of 0.097, P_f of 0.023. These results highlight the proposed method's superior ability to ensure accurate spectrum sensing with minimal interference.

Table 3. Comparison of TER and Channel Unavailability

	Total Error Rate	Channel Un-availability
KNN	12.801	42.802
NB	13.327	27.115
SVM	11.172	82.245
Stacked LSTM	4.534	11.00

In Table 3, Total Error Rate (TER) and Channel Un-availability is compared between models including KNN, NB, SVM and the Proposed Stacked LSTM. The Proposed Stacked LSTM has the lowest TER of 4.534, and the least amount of channel un-availability of 11.00. The Proposed Stacked LSTM performed the best, and by a large margin. The implication is that the model correctly minimize errors in prediction while providing channels with higher spectrum availability.

The proposed stacked LSTM model outperformed all other DL methods (CNN, Bi-LSTM, LSTM-ELM, and CNN-LSTM etc.) applying to temporal dependencies and are the most appropriate method to use in dynamic spectrum environments. The other listed models suffered in noisy environments, while the stacked LSTM model remained very stable and accurately predicted conditions in a SNR. The BER analysis signals the stacked LSTM highly reliable for transmission as it had slowly decreasing error rates, and experience little interference. Both results validate the stacked LSTM neural network model being the most robust and practical model for real-time spectrum sensing applications within CRN.

Conclusion

This paper concludes that, the utilization of Stacked LSTM network for spectrum sensing in CRN enables to overcome the issues of spectrum usage. The proposed model effectively achieves improved spectrum sensing accuracy even under inconsistent and fluctuating signal condition due to varying environmental circumstances. Furthermore, efficiency of proposed technique is evaluated using SNR and BER analysis, which indicates the efficacy of stacked LSTM. To validate this, GNURADIO and Python software are utilized and from the attained result it is understandable that, stacked LSTM attained highest prediction accuracy of 0.99, ensuring reduced interference with robust and effective detection of spectrum sensing in CRN. Also, compared to other models like LSTM-ELM and CNN-LSTM, the Stacked LSTM performs better in terms of efficiency, computation time, and convergence speed thus, paving way for more reliable and efficient wireless communication system including 5G applications.

Conflict of Interest

An authors have no conflicts of interest to declare that are relevant to the content of this article.

Author Contributions

Conceptualization: V. Kavitha;
Data curation: V. Kavitha;
Methodology: V. Kavitha and G. Seetharaman;
Project administration: G. Seetharaman;
Supervision: G. Seetharaman;
Validation: G. Seetharaman;
Writing-original draft: V. Kavitha;
Writing-review and editing: V. Kavitha and G. Seetharaman.

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References

Abdalzaher, M. S., Elwekeil, M., Wang, T., & Zhang, S. (2021). A deep autoencoder trust model for mitigating jamming attack in IoT assisted by cognitive radio. *IEEE Systems Journal, 16*(3), 3635–3645. https://doi.org/10.1109/JSYST.2021.3099072

Abusubaih, M. A., & Khamayseh, S. (2021). Performance of machine learning-based techniques for spectrum sensing in mobile cognitive radio networks. *IEEE Access, 10*, 1410–1418. https://doi.org/10.1109/ACCESS.2021.3138888

Almuqren, L., Maray, M., Alotaibi, F. A., Alzahrani, A., Mahmud, A., & Rizwanullah, M. (2024). Optimal deep learning empowered malicious user detection for spectrum sensing in cognitive radio networks. *IEEE Access, 12*, 35300–35308. https://doi.org/10.1109/ACCESS.2024.3367993

Arivudainambi, D., Mangairkarasi, S., & Kumar, K. V. (2022). Spectrum prediction in cognitive radio network using machine learning techniques. *Intelligent Automation & Soft Computing, 32*(3), 1525–1540. https://doi.org/10.32604/iasc.2022.020463

Chauhan, P., Deka, S. K., Chatterjee, B. C., & Sarma, N. (2021). Cooperative spectrum prediction-driven sensing for energy constrained cognitive radio networks. *IEEE Access, 9*, 26107–26118. https://doi.org/10.1109/ACCESS.2021.3057292

El-Shafai, W., Fawzi, A., Sedik, A., Zekry, A., El-Banby, G. M., Khalaf, A. A., & Abd-Elnaby, M. (2022). Convolutional neural network model for spectrum sensing in cognitive radio systems. *International Journal of Communication Systems, 35*(6), e5072. https://doi.org/10.1002/dac.5072

Hossain, M. S., & Miah, M. S. (2021). Machine learning-based malicious user detection for reliable cooperative radio spectrum sensing in cognitive radio–Internet of Things. *Machine Learning with Applications, 5*, 100052. https://doi.org/10.1016/j.mlwa.2021.100052

Kim, S. H., Kim, J. W., Nwadiugwu, W. P., & Kim, D. S. (2021). Deep learning-based robust automatic modulation classification for cognitive radio networks. *IEEE Access, 9*, 92386–92393. https://doi.org/10.1109/ACCESS.2021.3091421

Liu, M., Zhang, H., Liu, Z., & Zhao, N. (2022). Attacking spectrum sensing with adversarial deep learning in cognitive radio-enabled Internet of Things. *IEEE Transactions on Reliability, 72*(2), 431–444. https://doi.org/10.1109/TR.2022.3179491

Liu, X., Jia, M., Zhou, M., Wang, B., & Durrani, T. S. (2021). Integrated cooperative spectrum sensing and access control for cognitive industrial Internet of Things. *IEEE Internet of Things Journal, 10*(3), 1887–1896. https://doi.org/10.1109/JIOT.2021.3137408

Mishra, Y., & Chaudhary, V. S. (2023). Spectrum sensing in cognitive radio for Internet of Things using deep learning models. *SAMRIDDHI: A Journal of Physical Sciences, Engineering and Technology, 15*(1), 27–33. https://doi.org/10.18090/samriddhi.v15i01.04

Mohanakurup, V., Baghela, V. S., Kumar, S., Srivastava, P. K., Doohan, N. V., Soni, M., & Awal, H. (2022). 5G cognitive radio networks using reliable hybrid deep learning based on spectrum sensing. *Wireless Communications and Mobile Computing, 2022*(1), Article 1830497. https://doi.org/10.1155/2022/1830497

Nasser, A., Chaitou, M., Mansour, A., Yao, K. C., & Charara, H. (2021). A deep neural network model for hybrid spectrum sensing in cognitive radio. *Wireless Personal Communications, 118*(1), 281–299. https://doi.org/10.1007/s11277-020-08013-7

Obite, F., Usman, A. D., & Okafor, E. (2021). An overview of deep reinforcement learning for spectrum sensing in cognitive radio networks. *Digital Signal Processing, 113*, 103014. https://doi.org/10.1016/j.dsp.2021.103014

Sairam, M. V. S., Egala, R., & Nohith, K. S. (2024). Deep learning framework for enhancing the performance of cognitive radio network. *Journal of Emerging Technologies and Innovative Research, 11*(11).

Saraswathi, M., & Logashanmugam, E. (2024). Chicken swarm optimization modelling for cognitive radio networks using deep belief network-enabled spectrum sensing technique. *PLOS ONE, 19*(8), e0305987. https://doi.org/10.1371/journal.pone.0305987

Tekbıyık, K., Akbunar, Ö., Ekti, A. R., Görçin, A., Kurt, G. K., & Qaraqe, K. A. (2021). Spectrum sensing and signal identification with deep learning based on spectral correlation function. *IEEE Transactions on Vehicular Technology, 70*(10), 10514–10527. https://doi.org/10.1109/TVT.2021.3109236

Varun, M., & Annadurai, C. (2022). Intelligent spectrum sensing using optimized machine learning algorithms for cognitive radio in 5G communication. *Journal of Internet Technology, 23*(4), 827–836. https://jit.ndhu.edu.tw/article/view/2732

Venkatapathi, P., Khan, H., Rao, S. S., & Immadi, G. (2024). Cooperative spectrum sensing performance assessment using machine learning in cognitive radio sensor networks. *Engineering, Technology & Applied Science Research, 14*(1), 12875–12879. https://doi.org/10.48084/etasr.6639

Vijay, E. V., & Aparna, K. (2024). Deep learning-CT based spectrum sensing for cognitive radio for proficient data transmission in wireless sensor networks. *e-Prime: Advances in Electrical Engineering, Electronics and Energy, 9*, 100659. https://doi.org/10.1016/j.prime.2024.100659

Wang, K., Chen, Y., Bo, D., & Wang, S. (2025). A novel multi-user collaborative cognitive radio spectrum sensing model: Based on a CNN–LSTM model. *PLOS ONE, 20*(1), e0316291. https://doi.org/10.1371/journal.pone.0316291

Ye, H., & Jiang, J. (2021). Optimal linear weighted cooperative spectrum sensing for clustered-based cognitive radio networks. *EURASIP Journal on Wireless Communications and Networking, 2021*(1), Article 84. https://doi.org/10.1186/s13638-021-01977-5