Sqrt-Loglogish CNN and Markov model for 5G spectrum sensing application

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Article Info

Article history:

Received Feb 24, 2024
Revised Mar 10, 2024
Accepted Apr 13, 2024

Keywords:

5G spectrum
Cognitive radio
Deep learning
Fuzzy Markov model
Wideband spectrum sensing

ABSTRACT

The research presents innovative methods for spectrum sensing in 5G networks, using the Sqrt-Loglogish convolutional neural network (SL-CNN) and hidden orthogonal intuitionistic fuzzy Markov model (HOIFMM). The proposed methods aim to tackle issues related to detecting principal user signals accurately, mitigating interference, and efficiently utilizing the spectrum in wideband spectrum environments due to their diverse and ever-changing characteristics. The Sqrt-Loglogish CNN improves spectrum sensing by addressing static threshold dependency and potential overfitting. The HOIFMM offers a complex framework for predicting sparsity levels and primary user patterns. The results highlight the effectiveness of the suggested techniques in differentiating primary user signals from noise and interference, resulting in enhanced interference management tactics and overall network performance. MATLAB simulation is performed and compared the proposed methods performance with existing state-of-the-art methods such as CNN, deep neural network (DNN), long short-term memory (LSTM) and artificial neural networks (ANN). The proposed method has outperformed existing methods in terms of sensitivity, accuracy, and precision. Future endeavors include improving these methods, investigating sophisticated machine learning algorithms, and doing real-world validations to guarantee scalability and resilience in various 5G deployment situations. This research advances the spectrum sensing capabilities in 5G networks, potentially improving efficiency, reliability, and quality of service.

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1. INTRODUCTION

Communication technologies have progressed through important milestones, each promising higher speed, capacity, and connectivity than their predecessors. The advent of 5G networks is the most recent advancement in this trend, with the potential to transform how we communicate, interact, and connect with our surroundings [1], [2]. At the heart of the 5G revolution is the efficient use of the radio spectrum, a scarce resource on which wireless communication systems rely to deliver data, voice, and multimedia content. To appreciate the significance of 5G networks and the function of spectrum sensing within this paradigm, we must first examine the growth of wireless technologies and the issues they encounter. The journey began in the 1980s with the introduction of first-generation (1G) analogue cellular networks, which provided mobile phone communication, but lacked the data capabilities that current wireless networks require. Subsequent generations, such as 2G, 3G, and 4G LTE, saw gradual gains in data speeds, network capacity, and multimedia capability, paving the way for the mobile internet [3].

However, as demand for wireless data services grew and the number of connected devices increased, the limitations of existing wireless technologies became more evident. The spectrum scarcity, defined as the limited availability of radio frequencies appropriate for wireless communication, has arisen as a serious barrier to satisfying the expanding demands of users and applications [4]. Traditional static spectrum allocation strategies, which assign fixed frequency bands to licensed users, have proven ineffective in the face of dynamically shifting consumption patterns and bandwidth availability [5]. Cognitive radio (CR), a revolutionary idea that promises to alleviate spectrum shortages and inefficiencies by utilizing intelligent and adaptive spectrum management strategies. Spectrum sensing, or a radio device's ability to detect and identify vacant or underutilized spectrum bands in its proximity, is important to CR technology [6]. CR systems can enhance spectral efficiency, improve network capacity, and decrease interference by taking advantage of these "white spaces" in the spectrum, thereby unleashing the radio spectrum's full potential [7].

Energy detection and feature-based detection are two spectrum sensing methods. Energy detection, which compares the received signal's power level to a threshold to determine if a principal user (PU) signal exists, is the simplest and most common method [8]. Energy detection is dependable and easy to implement; however, it has low sensitivity in low signal-to-noise ratio (SNR) settings. In contrast, feature-based identification algorithms extract and analyse signal properties to distinguish primary and secondary users. Complex signal processing, machine learning (ML), and statistical models detect PU patterns and irregularities. In dynamic and heterogeneous conditions, feature-based detection surpasses energy detection, but it is more difficult and computationally intensive [9]. Next-generation wireless systems require spectrum sensing, making it crucial in 5G networks. 5G networks support a wide range of applications, including massive machine-type communication (mMTC) [10], ultra-reliable low-latency communication (URLLC) [11], and enhanced mobile broadband (eMBB) [12].

These diversified use cases place demanding demands on 5G networks, such as high data rates, low latency, enormous interconnectedness, and reliability, necessitating novel approaches to spectrum management and distribution. Spectrum sensing in 5G networks must deal with dynamic and diverse deployment scenarios in which numerous radio access technologies (RATs), frequency bands, and network operators exist and compete for spectrum resources. Furthermore, the expansion of internet of things (IoT) devices, smart sensors, and connected cars in 5G networks poses new challenges for spectrum access and interference reduction. Spectrum sensing techniques must be able to identify and adapt to quickly changing environmental circumstances, signal characteristics, and interference sources to provide optimal performance and quality of service (QoS) for a wide range of applications and consumers.

Given these issues and potential, this study proposes a novel spectrum sensing method for 5G networks using the Sqrt-Loglogistic convolutional neural network (SL-CNN) and the hidden orthogonal intuitionistic fuzzy Markov model (HOIFMM). Deep learning-based feature extraction, probabilistic modelling, and fuzzy logic reasoning provide a comprehensive and adaptive spectrum sensing solution for dynamic and heterogeneous 5G environments. By reviewing and comparing methods, we prove that the proposed method outperforms others in detection accuracy, robustness to noise and interference, computational efficiency, and scalability. Proposed solution advances spectrum sensing technology to maximise 5G networks' spectral efficiency, reliability, and flexibility, ushering in a new era of wireless communication and networking.

The urgent necessity to tackle the inherent issues and restrictions of existing methodologies while capitalising on powerful computational tools justifies the recommended spectrum sensing strategy in 5G networks. CR systems rely on spectrum sensing methods, including energy detection and matched filtering, but they have limitations in detection accuracy, flexibility, and scalability, especially in dynamic and heterogeneous 5G settings [13], [14]. Our approach aims to improve detection accuracy in wireless settings with low SNR, severe interference, and rapidly changing propagation conditions. Under such conditions, conventional spectrum sensing algorithms often miss principal user signals, causing false alarms or missed spectrum access chances. This method uses deep learning-based feature extraction and SL-CNN to improve detection sensitivity and resilience, improving spectrum utilisation and network performance. Spectrum sensing techniques must be adaptable and flexible to satisfy 5G network requirements and deployment circumstances, which drives our solution. Different RATs, frequency bands, and network operators compete for spectrum resources in 5G networks, which have dynamic spectrum sharing and heterogeneous network architectures. Classic spectrum sensing methods often fail to adapt to complex and dynamic conditions, resulting in poor performance and wasted spectrum. The principled and adaptive reasoning under uncertainty, which incorporates the HOIFMM probabilistic modelling framework, allows CR systems to make real-time decisions based on changing environmental conditions and user requirements.

Existing methods for sensing the wideband spectrum don't predict sparsity or PU patterns, which are very important when the spectrum is heterogeneous and the occupancy patterns vary across bands. This variance may cause interference issues and compromise spectrum allocation accuracy. Common static threshold approaches based on uncertain noise levels may result in incorrect spectrum allocation since noise is unpredictable. Security concerns also hinder wideband spectrum sensing devices. Spectrum availability data is tainted by malicious users that propagate fake information to deceive fusion centres and other users. Such attacks can severely impact network performance and wireless connections. Multipath fading hinders spectrum sensing because several pathways modify radio signals. Due to obstructions scattering the core user signal, this distortion may cause false negatives or positives, lowering sensing accuracy. Some systems have a high peak-to-average power ratio (PAPR), which may distort signals. This issue has the potential to degrade signal quality and spectrum sensing frameworks. We must address these issues to enhance the accuracy, reliability, and security of wideband spectrum sensing in dynamic and heterogeneous wireless environments.

The proposed work aims to achieve several objectives to address the challenges outlined in the problem statement effectively. Firstly, utilizing the HOIFMM to accurately estimate the sparsity level and PU pattern within the wideband spectrum. Subsequently, spectrum sensing will be conducted using SL-CNN to leverage the derived insights for enhanced detection accuracy. Additionally, deploying variance inflation factor lasso regression (VLR) to effectively manage the issue of noise uncertainty, ensuring more robust and accurate spectrum allocation. Furthermore, leveraging SL-CNN to detect and mitigate primary user emulation attacks, safeguarding the integrity of spectrum availability information and enhancing the security of the wireless network. Lastly, implementing hybrid beamforming with spatially homogeneous orthogonalization (HBSHO) techniques to mitigate the impact of multipath fading, thereby enhancing the reliability of spectrum sensing results.

2. RELATED WORKS

CR optimises the electromagnetic spectrum while taking advantage of changing spectrum opportunities. Optimizing spectral efficiency, CR systems discover unused radio frequency spectrums and dynamically modify their parameters. In CR networks, cognitive entities with changeable spectrum access are secondary users, and legally licenced corporations with exclusive spectrum rights are PUs [15], [16]. In CR, narrowband and wideband spectrum sensing are used [17], [18]. Spectrum sensing is key in CR. The literature describes spectrum sensing methods, including sub-Nyquist sampling using sparse fast fourier transform (sFFT), energy detection, and matching filtering. Simple and versatile energy detection technologies stand out. Low signal-to-noise ratios limit their performance. Cyclostationary and fresh energy detection methods may increase performance and reliability in demanding wireless settings [19], [20]. 5G wideband CR transmitter-receiver framework by Liu *et al.* [21]. They eliminate interference and increase transmission efficiency with cooperative spectrum sensing. To determine spectral availability, all CR users apply an inverse fast fourier transform (IFFT) to the product of a spectrum marker vector and a random phase vector. This method generates CR network spectrum utilisation subbasis functions. A detailed survey on CR network (CRN)-improved spectrum sensing in 5G wireless networks [22]. Authors examined traditional spectrum sensing technologies and difficulties in this paper. Next, sparsity acquisition, and reconstruction-based spectrum sensing models were examined. CRNs using orthogonal frequency-division multiplexing (OFDM) and CRN-cooperative spectrum sensing (CRN-CSS) must efficiently distribute resources due to spectrum sensing and transmission interference. Spectrum identification and resource allocation reduce interference and improve data transmission dependability [23]. The two-stage multi-slot channel assignment method blocks spectrum sensor interference. The study also minimises energy spectral density-based energy detection and spectrum sensing mistakes. In OFDM-based CRN-CSS, these algorithms optimise resource use and reduce data transmission interference.

SNR variations damage energy detectors. Cyclo-stationary detectors work but are hard to deploy. Matching filters require PU signal understanding. Mohanakurup *et al.* [24] suggested long short-term memory-extreme learning machine (LSTM-ELM) for these restrictions. Energy, distance, and duty cycle time are used to discover temporal patterns in spectral data via this hybrid approach. Time series prediction is revolutionised by the hidden Markov model (HMM) and fuzzy modelling technique [25]. Like rule-based models, it quantifies input-output time series data relationships using fuzzy rules. HMMs may describe multivariate time series data temporal dynamics and fluctuations, unlike fuzzy rule-based models. The proposed model outperforms fuzzy rule-based models without HMMs in experiments. HMMs improve the model's estimation of time series data's temporal features. HMM is a popular time series generative ML approach. A maximum a posteriori (MAP) framework was used to infer parameters [26]. Instead of Baum-Welch, priors regularise estimation. Authors use feature selection to improve system capabilities. Particle swarm optimization (PSO)-optimized HMM predicted fuzzy time series [27]. Smoothing removed zeros from observation events to improve accuracy. Monte Carlo simulation confirmed the method's stability and efficacy following prediction. This study uses HOIFMM to estimate spectrum sparsity and PU activity. This system is simple to build and use. Additionally, its adaptability allows rapid pattern analysis from raw data inputs of various lengths.

ML uses feature selection to build models. It lowers variation to improve model interpretation and generalisation. Recent decades have seen ridge regression, LASSO, and their variants in the literature. These strategies improve model performance and data analysis in several applications [28]. For several variance estimators, asymptotic investigations demonstrate consistency and normalcy under multiple assumptions. Many of these estimators show significant biases in small samples, especially when per-element signal strength increases and the genuine underlying signals become less sparse. Interestingly, a residual sum of squares estimator using LASSO coefficients and adaptive regularisation was understudied [29]. Traditional LASSO regression using Pythagorean fuzzy sets is used for system reliability studies. Decision-makers use Pythagorean fuzzy multivariate regression analysis to detect correlations between fuzzy or non-fuzzy interpretative factors. The Pythagorean fuzzy LASSO regression model is best for non-informative data [30]. Researchers study the limits and predictive regression applications of LASSO algorithms. They found that adaptive LASSO works but cannot asymptotically eliminate all integrating variables with zero regression coefficients [31]. A functional LASSO penalty gradually zeros coefficients, making the estimator sparse. Two roughness penalties smooth the final estimator's curvature. A significant study shows estimators maintain estimate and pointwise sign consistency. Smooth-LASSO accurately finds coefficient function zeroes and softly estimates non-zero values, enhancing model interpretability [32]. This study uses LASSO regression to address noise uncertainty. LASSO regression simplifies models and reduces uncertainty. Variable multicollinearity makes weight values confusing. The variance inflation factor (VIF) decreases LASSO regression multicollinearity and increases weight value interpretability. Harris hawk optimizer (HHO) is a modern hawk hunting-inspired population-based metaheuristic algorithm [33]. This optimizer uses swarm-based approaches and a revolutionary multi-search-phase exploration and exploitation strategy to optimise issues. Existing algorithms often get trapped in local search areas while optimising constrained engineering jobs. Kamboj *et al.* [34] explores the conventional HHOs exploration phase to improve global search and eliminate local optima constraint. Sine-cosine hybrid HHOs exist. The hybrid Harris hawks-sine cosine algorithm helps optimizers avoid local optima in complex search spaces. Two key improvements boost HHO algorithm performance. In the HHO algorithm's early phase, chaotic maps improve population variation in the search space. Second, simulated annealing (SA) enhanced HHO's optimal solution exploitation. A revised technique was tested on 14 medical benchmark datasets to show medical optimization potential [35].

Spectrum is allocated when the PU is not attacked. When the PU is attacked, the signal gets transmitted through the channel. An equalizer is used to reduce multipath fading in OFDM communications. HHO is used to tackle multipath fading due to its balanced exploration and exploitation and quick convergence speed. However, Harris hawk's optimization is susceptible to multiple local optima methods. Harris-hawks optimization (HBSHO) uses the Bernoulli shift map approach to overcome this limitation.

3. PROPOSED METHOD

3.1. Dataset used and preprocessing

The dataset included 500,000 transmissions across 16 subbands. This dataset mimics LTE-M uplink transmissions on PUSCH over 10 MHz using MATLAB's LTE Toolbox [36]. All 16 non-overlapping spectrum subbands were user-allocated channels. Figure 1 shows simulated transmission band spectrograms without and with channel effects at 20 dB SNR. A shared non-line-of-sight channel is simulated using additive white gaussian noise and Rayleigh fading in each transmission. The scenario is more complex and authentic since these alterations reflect channel conditions and confound categorization. early data preparation requires estimating missing values and normalising data. Missing dataset values are imputed using the feature mean. Normalising data removes unstructured and unneeded information and ensures field uniformity. Normalising the dataset improves analysis and modelling. After preprocessing, quadrature amplitude modulation (QAM) modulates the normalised signal. Wireless communication technologies raise baseband signal frequency with QAM modulation [37]. QAM modulation boosts wireless network capacity by boosting message delivery frequency. To reduce signal fading and loss, long-distance wireless communication requires this improvement. Wireless communication systems increase signal delivery and reliability with QAM modulation.

3.2. The estimation of sparsity level

Estimating spectrum sparsity and PU activity simultaneously with the Hidden orthogonal Markov model. Spectral occupancy patterns and PU activities are comprehensively analyzed using this method.

Hidden orthogonal Markov models show spectrum sparsity and activity [38]. These insights help with spectrum sensing and allocation decisions, which improve wireless resource management and network performance. This model helps us understand complex spectrum patterns and make judgements to increase spectrum usage and wireless communication system reliability. The simplicity, quickness, and convenience of implementation make this method suitable for real-time applications. It can discover patterns in raw data and handle different-length input data. Its failure to capture high-order correlations limits it [39]. Calculating the correlation coefficient with intuitionistic fuzzy sets eliminates this issue and enables more data conjunction analysis. Intuitional fuzzy sets reveal microscopic connections that previous methods neglected, improving pattern recognition and analysis. The HOIFMM evaluates spectrum sparsity and the PU activity pattern. A complex framework for spectrum characteristics and user behaviour analysis utilizing intuitionistic fuzzy logic and Markov modelling, HOIFMM. With HOIFMM, we are able to understand the dynamic spectrum and make sensible spectrum management and allocation decisions. This model shows intricate spectrum interactions, boosting wireless resource usage and network performance. HOIFMM analyses current wireless setups for spectrum distribution and connection.

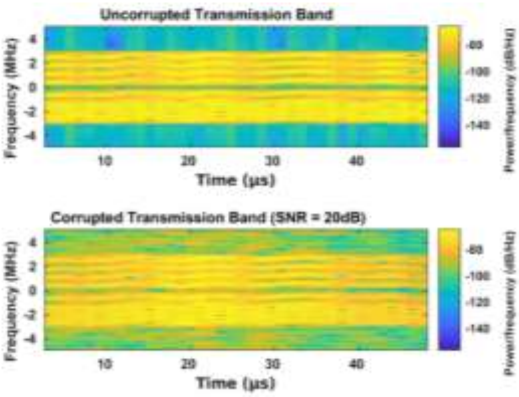


Figure 1. Spectrogram of a simulated transmission band

3.3. Spectrum sensing and classification model

This work extracts signal energy, eigenvalues, temporal correlation, frequency, bandwidth, and coding rate to identify spectrum users. Spectrum sensing CNNs get features and major user pattern details. CNNs are chosen for their ability to learn complex patterns from many samples. They can overfit, which can harm model performance. The square root of Loglogish is used to activate the SL-CNN. This modification reduces CNN model overfitting by reducing its tendency to memorise noise or irrelevant training data patterns. CNN is more resilient and can apply patterns to new data with this update. The CNN output predicts a spectrum principal user using the Sqrt-Loglogish activation function [40]. This predictive ability directly assigns unused spectrum to secondary users, maximising resource utilisation and reducing interference. This effective spectrum allocation strategy maximises spectrum use to improve wireless communication networks. The proposed model architecture is shown in Figure 2.

3.4. Spectrum allocation and attack detection

Various features such as PU position, PU emulation position, SU position, received power at the SU, estimated the distance between PU emulator attacker and SU, and estimated the distance between PU and SU are extracted and used to detect attacks within the spectrum. These attributes influence attack detection. The Sqrt-Loglogish CNN developed for PU detection is now employed for spectrum attack detection. The trained CNN model’s ability to detect data patterns and abnormalities is used to detect threats. Using the same CNN architecture for PU and attack detection improves analytical performance and consistency. Knowing the dataset and its features helps the model spot harmful anomalies. This comprehensive solution simplifies detection by eliminating the need for job-specific algorithms or models. Current CNN approach decreases computing complexity, optimises resource allocation, and improves threat detection speed and reliability. Using a single approach to identify PU and attacks helps the system adapt to shifting threat situations. Spectrum management methods must adapt to new threats and vulnerabilities to be effective. The use of SL-CNN for threat detection shows how deep learning can defend wireless communication systems.

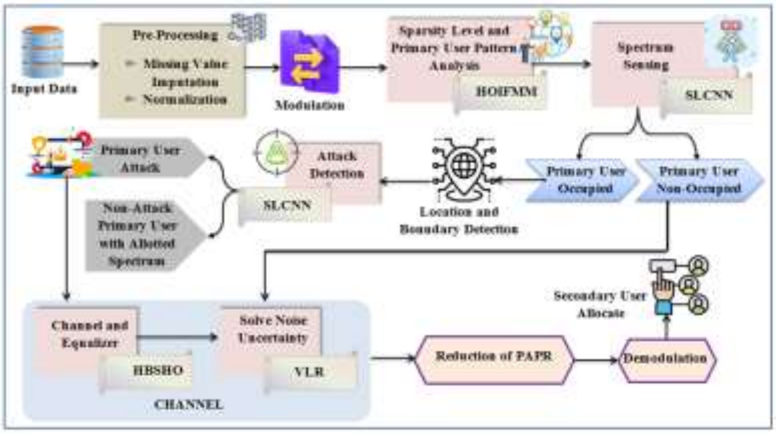


Figure 2. Proposed spectrum sensing architecture

3.5. Handling the multipath fading effect and noise uncertainties

When the PU is not attacked, spectrum is used for transmission. Attacked PUs send their signal across the channel. Multipath fading can occur during OFDM signal transmission due to signal propagation across numerous paths. Equalisers reduce channel multipath fading. Multipath distortion is corrected by equalisation, improving signal transmission reliability. HHO addresses multipath fading. This optimisation technique is chosen for its ability to balance exploration and exploitation, enabling convergence to optimal solutions. However, HHO may have multiple local optimal solutions, which may slow convergence [41]. To overcome this constraint, the HBSHO strategy uses the Bernoulli shift map in the HHO procedure. The Bernoulli shift map increases the optimisation algorithm's exploration [42], making globally optimal solutions easier to identify and diminishing local optimality. Multipath fading can be addressed with the HBSHO technique, ensuring reliable OFDM channel signal delivery. This complete solution boosts wireless communication network efficiency and robustness, especially in multipath propagation zones. LASSO regression addresses system noise uncertainty. LASSO regression reduces uncertainty and simplifies models. Multicollinearity in input variables makes weight values difficult to grasp in LASSO regression [43]. The LASSO regression framework addresses this issue and improves regression model interpretability by include the VIF. VIF detects and reduces multicollinearity, improving regression precision and reliability. The receiving end demodulates the signal after regression. The modulated signal is demodulated to prepare it for processing or analysis. SU receives the spectrum from the demodulated transmission. This allocation mechanism lets SU use the spectrum for communication, enhancing spectrum utilisation and network efficiency. LASSO regression, VIF, and modulation help the system control noise uncertainty and optimise secondary user spectrum allocation. This integrated technique improves wireless communication system reliability and productivity, ensuring spectrum efficiency. The proposed spectrum sensing model algorithm is shown in Figure 3.

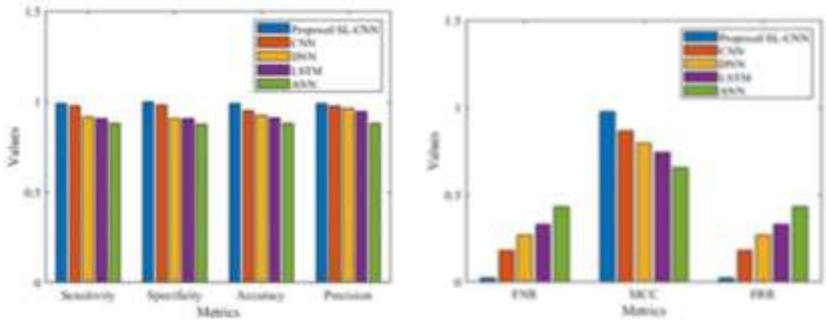
4. RESULTS AND DISCUSSION

The MATLAB implementation of proposed spectrum sensing and attack detection system provided useful performance insights. Its ability to identify PU, detect threats, and manage spectrum allotment has been verified through rigorous testing. The spectrum sensing model, which employs the proposed SL-CNN architecture, achieved good accuracy and reliability in distinguishing between occupied and unoccupied bands. Figure 4 demonstrates the classifier performance comparison among other state-of-art methods. The proposed strategy outperformed CNN, DNN, LSTM, and artificial neural network (ANN) methods in terms of sensitivity, specificity, accuracy, and precision as shown in Figure 4(a).

Multiple elements contribute to the proposed SL-CNN model's exceptional performance. The SL-CNN design increases feature extraction and pattern identification, enabling the model to distinguish between key user inputs and noise. Unique approaches, such as the Sqrt-Loglogish activation function, can reduce overfitting and improve model performance. Using modern signal processing and optimisation algorithms improves the practical reliability of the proposed SL-CNN model. The proposed method considers noise uncertainty, multipath fading, and other environmental factors to enable precise spectrum sensing and detection of harmful actions. Figure 4(b) depicts the suggested model's false negative rate (FNR), Matthew's correlation coefficient (MCC), and FRR. By significantly lowering FNR and false rejection rate (FRR), the proposed SL-CNN model effectively eliminates false negatives and rejections compared to previous approaches. The proposed SL-CNN model detects spectrum primary users and assaults with FNR and FRR values of 0.026. Because of the risk of missing critical messages or rejecting authorised users, wireless networks require higher capacity to offer dependable and secure communication. At 0.976, the MCC outperforms the other approaches. The MCC evaluates binary classification model performance by calculating true positives, true negatives, false positives, and false negatives. The high MCC value indicates that the proposed model's predictions correspond to real observations, demonstrating its reliability in spectrum sensing and attack detection.

1. Preprocess the data:
   - Read the data from each file using h5read.
   - Apply missing value imputation using movmedian.
   - Separate target labels and features.
   - Normalize the features.
2. Train and test spectrum sensing model using Proposed-SLCNN:
   - For each file in the dataset:
     a. Prepare the training and testing data.
     b. Train the SL_CNN_net using the training data.
     c. Test the trained model on the testing data.
     d. Evaluate the model's performance metrics (Sensitivity, Specificity, Accuracy, etc.).
3. Perform primary user location and boundary detection:
   - Locate PU and SU based on training data.
   - Utilize K-means clustering to identify boundary regions.
4. Detect attacks within the spectrum:
   - Calculate distances between PU and SU locations.
   - Apply Harris-Hawks optimization to mitigate multipath fading effects.
   - Integrate Bernoulli shift map to improve optimization convergence.
5. Train and test attack detection model using Proposed-SLCNN:
   - Prepare specific training and testing datasets for attack detection.
   - Train the SL_CNN_ADnet using the training data.
   - Test the model's performance on the testing data.
   - Evaluate the model's effectiveness in detecting attacks.
6. Implement channel equalization and noise uncertainty handling:
   - Generate training sequence and add noise to simulate channel conditions.
   - Use Lasso regression with Variance Inflation Factor to address noise uncertainty.
   - Apply clipping to manage peak-to-average power ratio (PAPR).
   - Demodulate the received signal and allocate spectrum based on availability.
7. Evaluate overall performance metrics:
   - Analyse sensitivity, specificity, accuracy, precision, recall, F-measure, etc., for both spectrum sensing and attack detection models.

Figure 3. Algorithm of proposed spectrum sensing model



(a) (b)

Figure 4. Classifier performance comparison (a) interms of sensitivity, specificity, accuracy, and precision; and (b) interms of FNR, MCC, and FRR

The evaluation of the PU location and boundary detection methods provided important information on the system's ability to accurately define PU areas and SU limits, as shown in Figure 5. The system demonstrated its ability to effectively identify major user locations and delineate border zones by utilizing advanced spatial analytic techniques like K-means clustering. This feature allows for accurate identification of PUs in the spectrum and helps in implementing effective spectrum allocation and management techniques. The system uses advanced geographical analysis to efficiently allocate available frequency bands to SUs, minimizing interference with PU broadcasts. Integrating advanced spatial analytic techniques improves the performance and effectiveness of the spectrum sensing and management system, making it suitable for deployment in dynamic wireless situations.

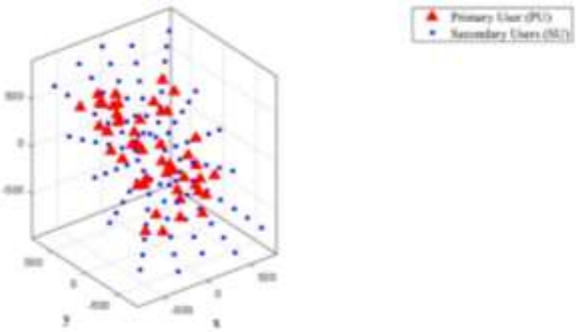


Figure 5. PU and SU boundary mapping

The addition of channel equalization and noise uncertainty handling algorithms significantly improves the system's robustness and reliability in wireless communication. The system effectively tackled issues caused by noise uncertainty and multipath fading effects by using advanced signal processing techniques including LASSO regression and VIF. Channel equalization techniques are crucial for reducing the negative impact of channel distortion, especially in situations where signal dispersion and distortion occur due to multipath propagation. Utilizing suitable equalization algorithms like adaptive equalization or zero-forcing equalization can help the system counteract channel impairments and improve the accuracy of received signals, thereby enhancing communication reliability. Figure 6 demonstrates the received signal and the equalized signal.

LASSO regression combined with VIF is an effective method for managing noise uncertainty in wireless communication networks. LASSO regression is a regularization method that helps the system assess and reduce the influence of noise on signal quality by penalizing high model complexity and promoting sparsity in the regression coefficients. The system can improve the estimate process and enhance the accuracy of noise mitigation measures by using VIF as a measure of multicollinearity among predictor variables. The equalization procedure corrects the received signal by adjusting it according to the channel's characteristics and the known transmission parameters. This may include methods like inverse filtering or adaptive equalization, which seek to estimate and counteract the impacts of channel distortion. The fitness figures indicate the HBSHO optimization function's performance at various iterations during the optimization process. Smaller fitness values indicate superior performance, as they reflect a closer proximity to the optimal solution, HBSHO optimization performance is compared in Figure 7.

In this case, observed that the fitness values decrease from 3.5 to 0 as the optimization process progresses through iterations. The trend indicates that the HBSHO algorithm effectively optimizes system parameters to reduce the impact of multipath fading. The technique efficiently reduces distortion and signal deterioration from multipath propagation, resulting in enhanced signal quality and dependability. Integrating the Bernoulli shift map into the HBSHO technique improves its capacity to explore the search space and reach optimal solutions efficiently. The HBSHO method combines the unique features of HHO with the Bernoulli shift map to effectively tackle multipath fading issues in wireless communication systems, showcasing resilience and effectiveness.

Comparing DeepSense [36], which uses a traditional CNN algorithm, with our suggested solution, which incorporates a hybrid model designated SL-CNN with HOIFMM, as well as noise mitigation and attack detection techniques, demonstrates significant progress in spectrum sensing for 5G networks. The new method proposed shows significant advantage over DeepSense in precision, with a score of 0.9902 compared to DeepSense's 0.84. This indicates improved accuracy in detecting primary user signals and minimizing false positives, crucial for enhancing spectrum utilization. Moreover, this method shows higher memory and F-measure scores, with a recall value of 0.9891 compared to DeepSense's 0.87. This highlights the efficiency of our approach in precisely identifying principal user signals while reducing instances of missed detections, therefore improving interference management and overall network dependability. The comparison is summarized in Table 1. The notable performance enhancement attained by the novel hybrid SL-CNN with HOIFMM model highlights the effectiveness of combining CNNs and HMMs. Moreover, implementing noise mitigation and attack detection algorithms improves the resilience and dependability of spectrum sensing in 5G networks.

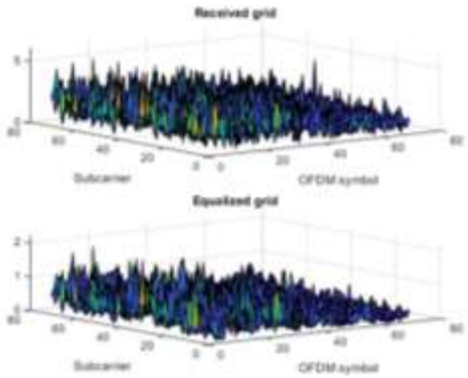


Figure 6. LASSO regression with VIF in handling noise

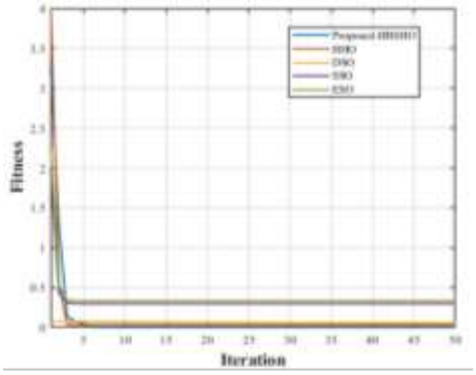


Figure 7. Performance of the proposed optimization method

Table 1. Performance comparison with the base model

	Precision	Recall	F-measure
DeepSense [36]	0.84	0.87	0.86
Ours	0.990268966	0.989091327	0.981955729

5. CONCLUSION

This paper has introduced novel methods for spectrum sensing in 5G networks, utilizing the SL-CNN and HOIFM model. The proposed methods have shown significant success in reliably recognizing primary user signals in the presence of noise and interference, allowing for more efficient interference mitigation strategies. This study emphasizes the need to utilize enhanced spectrum sensing techniques to improve the efficiency and dependability of 5G networks. The proposed methods, utilizing advanced algorithms and models, have demonstrated great potential in enhancing spectrum utilization, minimizing interference, and optimizing resource allocation. This results in improved network capacity and QoS. The future direction of this research includes enhancing and perfecting suggested solutions to tackle new issues and demands in 5G networks. This involves investigating new machine learning methods, improving signal processing techniques, and incorporating sophisticated cognitive abilities to provide smarter and more adaptable spectrum sensing solutions. The ideas and contributions in this paper provide a strong basis for progressing the topic of spectrum sensing in 5G networks, with potential benefits for enhancing network efficiency, dependability, and quality of service. Continuing to improve and develop spectrum sensing techniques will enable us to fully utilize the capabilities of 5G technology and facilitate a more interconnected and smarter future.

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