# Deep Learning-Based Spectrum Occupancy Prediction in 6G Networks

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***Abstract*-The rapid evolution toward sixth-generation (6G) wireless networks is expected to support ultra-high data rates, massive device connectivity, holographic communications, and intelligent services. Efficient utilization of the radio frequency spectrum becomes a critical challenge because traditional static allocation strategies cannot cope with the dynamic and heterogeneous traffic patterns of future networks. Spectrum occupancy prediction using deep learning emerges as a promising solution to proactively estimate channel usage and enable intelligent spectrum access for cognitive radios and network controllers. This project proposes a deep learning–based framework for predicting spectrum availability in 6G environments by analyzing historical sensing data, temporal traffic variations, and spatial features. Advanced neural architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Networks (CNN) are employed to capture time–frequency correlations and non-linear patterns in spectrum usage. The system integrates data preprocessing, feature extraction, model training, and real-time inference to assist dynamic spectrum allocation decisions. Performance is evaluated using metrics such as prediction accuracy, precision–recall, and spectral efficiency improvement. The proposed approach aims to reduce interference, minimize spectrum wastage, and enhance quality of service for next-generation applications, thereby contributing toward intelligent, autonomous, and energy-efficient 6G wireless communication systems.**

## I. INTRODUCTION

Sixth-generation (6G) wireless communication is envisioned to go beyond the capabilities of 5G by enabling terabit-per-second data rates, ultra-low latency, integrated sensing and communication, and artificial intelligence–driven network management. Such ambitious requirements impose severe stress on existing radio spectrum resources, making intelligent spectrum usage a fundamental research problem. Conventional spectrum management policies rely on fixed licensing or rule-based dynamic access, which often result in underutilized bands and inefficient sharing among heterogeneous users. Cognitive radio technology introduced the idea of opportunistic spectrum access; however, reactive sensing alone may not be sufficient in highly dynamic 6G scenarios.

Predictive spectrum analytics enables the network to forecast future channel states rather than merely reacting to current conditions. By leveraging historical usage patterns, traffic statistics, and contextual information, predictive models can proactively guide scheduling and allocation decisions. Deep learning has demonstrated remarkable success in modeling complex temporal and spatial relationships in wireless channels, traffic flows, and interference patterns. Recurrent and convolutional neural networks are particularly suitable for spectrum prediction due to their capability to learn long-term dependencies and frequency-domain features.

This Application focuses on designing and implementing a deep learning–driven spectrum occupancy prediction system tailored for 6G networks. The study covers dataset generation, model design, training and evaluation, and system integration to demonstrate the feasibility and effectiveness of intelligent spectrum management.

The emergence of sixth-generation (6G) wireless communication systems is expected to revolutionize global connectivity by enabling ultra-high data rates, sub-millisecond latency, massive machine-type communications, extended reality applications, and integrated sensing and communication services. These ambitious objectives demand unprecedented levels of intelligence and flexibility in radio resource management. Among the most critical challenges faced by future networks is the scarcity and inefficient utilization of radio frequency spectrum, which remains a limited and highly regulated natural resource. Traditional spectrum allocation strategies rely largely on fixed licensing policies, where specific frequency bands are permanently assigned to licensed operators. Although this approach guarantees reliability for incumbents, numerous measurement campaigns have revealed that many licensed bands remain underutilized in both time and space. Such inefficiencies become unacceptable in the context of 6G, where billions of heterogeneous devices—ranging from autonomous vehicles to smart factories and holographic displays—will compete for wireless access.

To overcome spectrum scarcity, dynamic spectrum access and cognitive radio technologies were introduced, allowing secondary users to opportunistically exploit idle channels without harming primary license holders. Cognitive radios perform spectrum sensing to detect vacant bands and adjust transmission parameters accordingly. However, most existing sensing-based approaches are reactive in nature; decisions are made only after observing current channel conditions, which may already be outdated in highly dynamic environments. Predictive spectrum management has therefore gained increasing attention as a proactive alternative. Instead of merely detecting instantaneous occupancy, predictive systems aim to forecast future channel usage by learning historical traffic patterns, temporal correlations, and spatial behaviors of wireless transmissions. Such forecasting capability enables base stations and network controllers to reserve resources in advance, schedule transmissions intelligently, and avoid harmful interference before it occurs.

Artificial intelligence, and particularly deep learning, has emerged as a powerful tool for modeling complex wireless phenomena. Unlike conventional statistical models that rely on simplifying assumptions, deep neural networks can automatically learn non-linear relationships from large-scale datasets. In the wireless domain, deep learning has already demonstrated impressive results in channel estimation, modulation classification, beamforming, traffic prediction, and network optimization, making it a natural candidate for spectrum occupancy prediction. Recurrent neural networks such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are especially effective for capturing temporal dependencies in sequential data, such as spectrum usage over time. Convolutional Neural Networks (CNN), on the other hand, are capable of extracting spatial and frequency-domain features from spectrogram representations of wideband signals. Hybrid architectures that combine these models can exploit both temporal and spectral correlations, leading to more accurate and robust predictions.

With the advent of 6G, additional complexities arise, including ultra-dense deployments, intelligent reflecting surfaces, non-terrestrial networks, terahertz communications, and edge intelligence. These features further increase the variability of spectrum usage patterns and require learning models that can scale to massive datasets while adapting in near real time. Consequently, spectrum prediction frameworks must be computationally efficient, resilient to noise, and capable of operating in distributed environments. Another important aspect of predictive spectrum management is the availability and preparation of data. Spectrum sensing measurements are often affected by fading, shadowing, noise uncertainty, and hardware imperfections. Therefore, data preprocessing, normalization, feature extraction, and labeling become crucial steps in building reliable learning-based systems. Synthetic data generation and simulation platforms also play a significant role in evaluating proposed solutions for futuristic 6G scenarios that do not yet exist in real deployments.

From a system-level perspective, accurate spectrum occupancy prediction can significantly enhance overall network performance. Proactive allocation reduces unnecessary sensing overhead, minimizes channel switching delays, lowers interference with licensed users, and improves spectral efficiency. Furthermore, such intelligence contributes to energy-efficient operation and supports autonomous network management, which is a key design philosophy of 6G architectures. This project focuses on designing and implementing a deep learning–based spectrum occupancy prediction framework specifically tailored for next-generation 6G networks. The work encompasses dataset creation, preprocessing pipelines, neural network architecture design, training and evaluation strategies, and real-time deployment considerations. By integrating predictive intelligence into spectrum management, the proposed system aims to contribute toward the realization of fully autonomous, adaptive, and efficient wireless networks for the future.

## II. EXISTING SYSTEM

In current wireless communication networks, spectrum management is largely governed by static licensing policies and conventional dynamic spectrum access techniques supported by cognitive radio technology. Licensed users are assigned fixed frequency bands for long-term use, while unlicensed or secondary users attempt to opportunistically access idle channels through periodic spectrum sensing. These systems typically rely on energy detection, cyclostationary feature detection, or matched filtering to determine whether a channel is occupied at a given moment. Decision making is mostly reactive—transmissions are scheduled only after sensing the instantaneous state of the spectrum—without considering future usage patterns. Some deployments employ basic statistical or time-series models, such as Markov chains or autoregressive methods, to estimate short-term occupancy trends; however, these models assume relatively stationary traffic behavior and limited environmental variation. As a result, present-day spectrum access mechanisms struggle to adapt to highly dynamic, ultra-dense network conditions envisioned for 6G, where traffic loads, mobility patterns, and interference levels change rapidly across time and space.

## III. EXISTING SYSTEM AND DISADVANTAGES

Reactive sensing approaches suffer from delayed decisions, vulnerability to hidden node problems, and frequent collisions with licensed users. Traditional statistical models such as Markov chains cannot capture complex non-linear traffic patterns, leading to poor prediction accuracy in dense and heterogeneous 6G environments.

1. Reactive Decision Making: Current systems primarily depend on real-time spectrum sensing rather than prediction, causing delays in access decisions and increasing the likelihood of collisions with licensed users in rapidly changing environments.
2. Low Prediction Accuracy: Traditional statistical models such as Markov chains and autoregressive methods assume stationary traffic patterns and fail to capture complex, non-linear spectrum usage behaviors present in ultra-dense and heterogeneous networks.
3. High Sensing Overhead: Continuous wideband spectrum sensing consumes significant energy and computational resources, especially for battery-powered devices and edge nodes operating in massive Internet-of-Things scenarios.
4. Hidden Node and Interference Problems: Imperfect sensing due to fading, shadowing, and noise uncertainty can lead to misdetections, resulting in harmful interference with primary users and reduced overall network reliability.
5. Poor Scalability for 6G Requirements: Existing frameworks struggle to scale with the extremely high device densities, diverse service types, and terahertz-frequency operations expected in 6G networks, limiting their ability to provide autonomous and efficient spectrum utilization.

## IV. PROPOSED SYSTEM

The proposed system introduces a deep learning–based predictive framework that analyzes historical wideband sensing data to forecast short-term and long-term spectrum occupancy. It integrates CNN layers for frequency-domain feature extraction with LSTM or GRU layers for temporal modeling, enabling proactive spectrum allocation decisions. The proposed system introduces an intelligent, deep learning–driven spectrum occupancy prediction framework specifically designed for next-generation 6G wireless networks. Instead of relying solely on instantaneous spectrum sensing, the system continuously learns from historical wideband sensing measurements, traffic statistics, and environmental context to forecast future channel usage across time and frequency dimensions. A hybrid neural architecture combining Convolutional Neural Networks (CNN) for spectral feature extraction with Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), or transformer-based models for temporal dependency modeling is employed to capture complex spatiotemporal correlations in spectrum utilization. The framework incorporates automated data preprocessing, noise filtering, normalization, and feature engineering to ensure robust model training under realistic channel conditions. Trained models are deployed at edge nodes or centralized controllers to enable real-time inference, supporting proactive spectrum allocation, interference avoidance, and adaptive scheduling decisions. By embedding predictive intelligence into radio resource management, the proposed system aims to enhance spectral efficiency, reduce sensing overhead, and facilitate autonomous, energy-efficient operation in future 6G communication environments.

## V. PROPOSED SYSTEM AND ADVANTAGES

The approach improves prediction accuracy, reduces interference, and increases spectral efficiency. Proactive allocation minimizes channel switching overhead, enhances quality of service, supports autonomous network operation, and adapts to evolving 6G traffic conditions in real time. Deep learning–based spectrum occupancy prediction framework offers several key advantages over conventional spectrum management approaches:

1. Proactive Spectrum Allocation: By forecasting future channel usage instead of reacting only to current sensing results, the system enables advance reservation of idle bands, significantly reducing collision probability and access delays.
2. Higher Prediction Accuracy: Hybrid CNN–LSTM/GRU or transformer-based architectures effectively model complex spatiotemporal patterns, leading to superior occupancy prediction performance in ultra-dense and heterogeneous 6G environments.
3. Reduced Sensing and Energy Overhead: Predictive intelligence minimizes the need for continuous wideband sensing, conserving computational resources and extending battery life for edge devices and Internet-of-Things nodes.
4. Improved Spectral Efficiency and QoS: Intelligent channel selection reduces interference with licensed users and maximizes utilization of available spectrum, thereby enhancing throughput, latency, and overall quality of service.
5. Scalability and Autonomy for 6G Networks: The system supports distributed edge deployment, online learning, and adaptive model updates, allowing it to scale to massive device densities and operate autonomously in highly dynamic future wireless ecosystems.

## VI.IMPLEMENTATION MODULES

1. Data Collection Module – Generates or collects spectrum sensing datasets.
2. Preprocessing Module – Cleans data, performs normalization, and extracts features.
3. Model Training Module – Trains CNN, LSTM, and hybrid architectures.
4. Evaluation Module – Computes accuracy, F1-score, and prediction error.
5. Real-Time Prediction Module – Deploys trained models for inference.
6. Visualization Dashboard – Displays occupancy maps and performance metrics.

## VII. IMPLEMENTATION ALGORITHMS

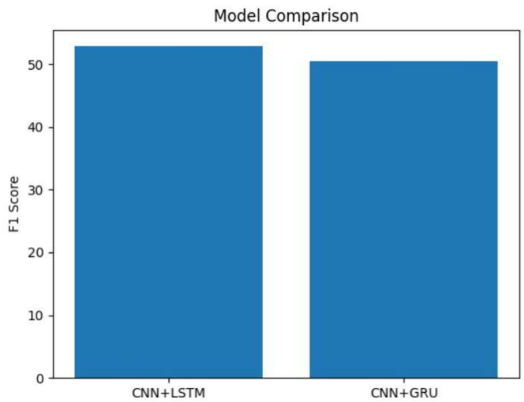
1. Data Acquisition & Spectrum Sensing Algorithm
Wideband sensing is performed using energy detection or cyclostationary feature detection.
Signal samples are collected across multiple frequency bands and time slots.
Power spectral density (PSD) is computed using Fast Fourier Transform (FFT).
Occupancy labels (idle/busy) are generated using adaptive thresholding.
Data is stored in time–frequency matrices for training.
Sliding-window segmentation is applied to form prediction sequences.

2. Data Preprocessing Algorithm
Noise reduction using moving average or median filters.
Normalization via Min-Max scaling or Z-score standardization.
Missing value handling through interpolation.
Time-series windowing for supervised learning.
Feature extraction (energy levels, variance, spectral entropy).
Dataset splitting into training, validation, and test sets.

3. CNN-Based Spectral Feature Extraction
Input spectrogram images are passed to convolutional layers.
ReLU activation functions introduce non-linearity.
Max-pooling reduces dimensionality.
Batch normalization stabilizes training.
Feature maps are flattened for temporal modeling.
Dropout is applied to avoid overfitting.

4. LSTM / GRU Temporal Prediction Algorithm
Sequential CNN features are fed into recurrent layers.
Memory gates capture long-term temporal dependencies.
Bidirectional variants improve future-state awareness.
Attention layers highlight critical time-frequency regions.

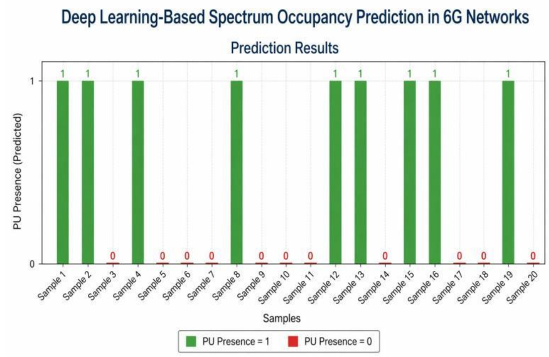
Dense layers produce final occupancy probabilities.
Sigmoid or softmax activation determines channel state.




5. Transformer-Based Prediction Algorithm (Optional Advanced)
Positional encoding is added to spectrum sequences.
Multi-head self-attention models global dependencies.
Encoder blocks stack for deeper learning.
Layer normalization stabilizes convergence.
Fully connected layers output predictions.
Suitable for long-horizon forecasting.

6. Model Training & Optimization Algorithm
Loss function: Binary Cross-Entropy or Categorical Cross-Entropy.
Optimizers: Adam, RMSProp, or SGD with momentum.
Learning-rate scheduling improves convergence.
Early stopping prevents overfitting.
K-fold cross-validation improves robustness.
GPU acceleration using CUDA.

7. Performance Evaluation Algorithm
Accuracy, Precision, Recall, F1-Score computed.
ROC-AUC analysis performed.
Confusion matrices generated.
Spectral-efficiency gain calculated.
Latency and throughput measured.
Comparative benchmarking with baseline models.
Trained models exported to ONNX or TensorFlow Lite.
Edge-deployment pipelines created.
Streaming spectrum frames processed.
Sliding window prediction performed online.
Decision engine selects best idle band.
Feedback loop updates datasets for retraining.




## VIII. SOFTWARE REQUIREMENTS

Development Tools: Python, Jupyter Notebook, VS Code.
AI Models: CNN, LSTM, GRU, Transformer.
Libraries: TensorFlow/Keras, PyTorch, NumPy, Pandas, Matplotlib, Scikit-learn.
Data Sources: Simulated spectrum traces, public wireless datasets.
Environment: Windows/Linux OS, CUDA-enabled GPU, Python 3.10+, virtual environment tools.

## IX. CONCLUSION

The project on Deep Learning-Based Spectrum Occupancy Prediction in 6G Networks demonstrates the importance of intelligent and proactive spectrum management for future wireless communication systems. Traditional spectrum allocation methods are inefficient and unable to handle the dynamic and complex requirements of 6G networks. To overcome these limitations, this work proposed a deep learning–based framework that combines advanced models such as CNN, LSTM, and GRU to accurately predict spectrum usage.
By analyzing historical and real-time data, the proposed system is capable of forecasting channel availability, enabling proactive decision-making instead of reactive sensing. This significantly reduces interference, improves spectral efficiency, and enhances overall network performance. The integration of data preprocessing, feature extraction, model training, and real-time prediction ensures that the system is robust, scalable, and suitable for deployment in next-generation networks.

Overall, this project highlights that deep learning plays a crucial role in enabling autonomous, efficient, and intelligent spectrum utilization in 6G environments. The proposed approach not only improves prediction accuracy but also supports energy-efficient and high-quality communication, making it a promising solution for future wireless technologies

REFERENCES

[1] J. Mitola and G. Q. Maguire, "Cognitive radio: Making software radios more personal," *IEEE Personal Communications*, vol. 6, no. 4, pp. 13–18, Aug. 1999.

[2] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 2, pp. 201–220, Feb. 2005.

[3] T. Yücek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Communications Surveys & Tutorials*, vol. 11, no. 1, pp. 116–130, First Quarter 2009.

[4] I. F. Akyildiz, W. Y. Lee, M. C. Vuran, and S. Mohanty, "Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey," *Computer Networks*, vol. 50, no. 13, pp. 2127–2159, Sept. 2006.

[5] K. B. Letaief and W. Zhang, "Cooperative communications for cognitive radio networks," *Proceedings of the IEEE*, vol. 97, no. 5, pp. 878–893, May 2009.

[6] H. Sun, A. Nallanathan, C.-X. Wang, and Y. Chen, "Wideband spectrum sensing for cognitive radio networks: A survey," *IEEE Wireless Communications*, vol. 20, no. 2, pp. 74–81, Apr. 2013.

[7] Z. Qin, H. Ye, G. Y. Li, and B.-H. F. Juang, "Deep learning in physical layer communications," *IEEE Wireless Communications*, vol. 26, no. 2, pp. 93–99, Apr. 2019.

[8] H. Ye, G. Y. Li, and B.-H. F. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Communications Letters*, vol. 7, no. 1, pp. 114–117, Feb. 2018.

[9] M. A. Aygül, H. A. Çırpan, and H. Arslan, "Machine learning-based spectrum occupancy prediction: A comprehensive review," *Frontiers in Communications and Networks*, vol. 6, 2025.

[10] G. Pan, Q. Wu, B. Zhou, G. Ding, and D. K. Y. Yau, "Spectrum prediction with deep 3D pyramid vision transformer learning," *arXiv preprint arXiv:2408.06870*, 2024.