Enhancing Spectrum Awareness in Cellular Networks Through Deep Learning Approaches for Efficient 5G-NR and LTE Signal Classification

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Abstract. Spectrum sensing is essential for future wireless communications, distinguishing 5G, Long-Term Evolution (LTE), and noise signals. It ensures effective coexistence by identifying and allocating available spectrum for diverse technologies. This capability optimizes network performance, mitigates interference, and facilitates seamless integration of IoT devices, enhancing overall communication efficiency and reliability. Recently deep learning (DL) architectures are vital for classifying 5G new radio (5G NR), LTE, and noise signals in wireless communication. They automate feature extraction, improving accuracy and spectrum management for seamless coexistence of diverse technologies. The paper presents two deep neural network architectures, Convolutional Neural Network (CNN) and VGG16, designed to discern between 5G NR and LTE signals. The primary objective is to enhance spectrum awareness by proficiently identifying distinct signal patterns within a cellular system environment. A comprehensive performance analysis of classifiers is conducted, leveraging with different optimizers. Additionally, the research investigates the impact of varying training rates on the classifiers' efficacy, contributing insights into their comparative superiority.

Keywords: Spectrum Sensing · Spectrum Awareness · Deep Learning · 5G NR · LTE · Signal Classification · CNN · VGG16

1 Introduction

In the rapidly evolving background of wireless communication, the effective classification of signals has become paramount for optimizing spectrum utilization and ensuring seamless coexistence of diverse technologies. The advent of 5G technology has piloted in a new era of connectivity with unprecedented speed and capacity. However, the coexistence of multiple wireless technologies and the presence of ambient noise pose challenges in spectrum management [1]. Traditional signal classification methods struggle to cope with the intricacies of 5G NR and LTE signals, as well as the interference from noise. Further, SS is a critical aspect of cognitive radio networks, enabling efficient and

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dynamic spectrum utilization. Traditional SS techniques often face challenges in adapting to dynamic and complex radio environments [2]. Classical methods such as energy detection, matched filtering, and cyclostationary feature analysis have been widely used. The limitations and shortcomings of these methods in addressing the challenges posed by dynamic and heterogeneous radio environments are highlighted.

Deep learning architectures, particularly neural networks, emerge as a game-changer in this context. Their ability to automatically extract intricate features and discern complex patterns makes them well-suited for the nuanced task of signal classification [3]. DL transforms communications signal waveform pattern recognition, enhancing efficiency and adaptability [4]. DL, especially convolutional and recurrent neural networks, excels in recognizing modulation schemes, aiding in dynamic spectrum allocation [5]. This finds applications in wireless communication systems, optimizing signal processing for various protocols like LTE, 5G NR, and beyond.

Identifying 5G NR and LTE signals in noisy environments has garnered significant research attention. Recent methodologies proposed by researchers employ advanced signal processing techniques and machine learning algorithms. These may include deep learning approaches, feature extraction methods, and adaptive filtering to enhance signal detection and classification accuracy. Evaluating these methods under diverse noise scenarios, researchers aim to improve the robustness and reliability of 5G NR and LTE signal identification, addressing challenges in real-world, dynamic wireless environments. Continuous advancements in this area contribute to the development of more resilient and adaptive communication systems, crucial for the evolving landscape of wireless technologies [6]. A DL based spectrum sensing approach for 5G NR and LTE signals, employing a semantic segmentation ConvNet [7]. Achieving 95% mean accuracy, it demonstrates robustness under diverse channel impairments in simulations. Neural networks are used to identify 5G signals amidst various cellular communications signals like LTE and UMTS. Exploring deep learning's effectiveness, it considers dataset size, extracted features, and channel fading, demonstrating successful signal identification [8].

By leveraging DL, this research aims to enhance the accuracy and efficiency of classifying 5G NR, LTE, and noise signals, ultimately contributing to optimal spectrum allocation and mitigating interference [9]. The insights gained from this work have far-reaching implications for the future of wireless communication, ensuring the robust coexistence of advanced technologies in the dynamic spectrum environment.

This paper follows the structured organization, beginning with an introduction highlighting the significance of 5G and LTE signal identification. Section II details the specifications of these signals. Section III focuses on DL architectures tailored for signal identification in noisy environments. Results and discussions are presented in Section IV, while Section V concludes the study, summarizing findings and suggesting future research directions.

2 Signal Characteristics and Research Framework

5G NR and LTE utilize distinct frequency bands to deliver wireless communication services, catering to diverse requirements and environmental conditions [10]. In the sub-6 GHz frequency range (FR1), 5G NR incorporates bands such as 600 MHz, 700 MHz, 2.1 GHz, 2.3 GHz, 2.5 GHz, and 3.5 GHz, enabling a balance between coverage and data rates. Additionally, the millimeter-wave (mmWave) frequency range (FR2) extends into bands like 24.25–29.5 GHz and 66–71 GHz, supporting high-capacity and low-latency applications in specific scenarios. Conversely, LTE spans various frequency bands, categorized into Frequency Division Duplex (FDD) and Time Division Duplex (TDD). Common FDD bands include 2100 MHz, 1900 MHz, 1800 MHz, and 700 MHz, while TDD bands encompass 2600 MHz, 2300 MHz, and 3500 MHz, among others. These bands empower LTE to offer reliable connectivity across diverse spectral landscapes. It's imperative to recognize that the allocation of specific bands is subject to regional regulatory decisions, and network operators tailor deployments to align with local requirements, ensuring optimal performance and coverage.

Detecting signals like LTE and 5G NR in noisy environments poses significant challenges due to the complex nature of the noise and the similarities between signal and noise characteristics. Noise can obscure or distort the signal, making it difficult to distinguish between them. Additionally, LTE and 5G NR signals often exhibit dynamic modulation schemes and frequency allocations, further complicating their identification amidst noise. Traditional detection methods may struggle to cope with these complexities, leading to decreased accuracy and reliability in signal detection. As a result, effective detection of LTE and 5G NR signals in noisy environments requires robust signal processing techniques and advanced algorithms capable of mitigating noise interference.

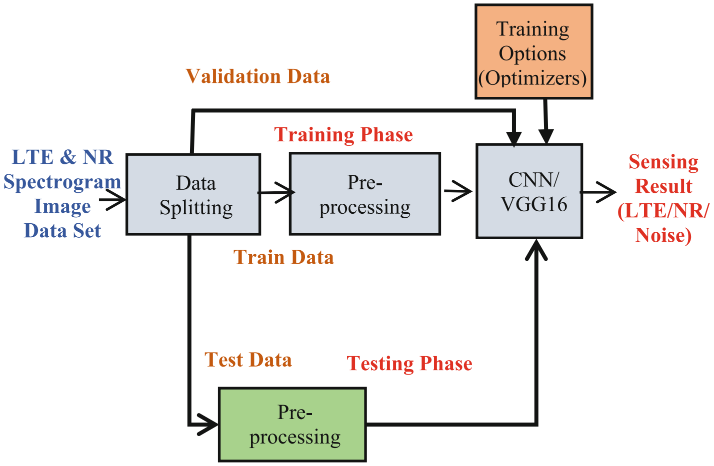

Fig. 1. Proposed Famework

Figure 1 depicts the proposed framework of the signal identification. The research framework outlined aims to address the pressing challenge of effective spectrum sensing and classification in the context of rapidly evolving wireless communication technologies such as 5G NR and LTE. Traditional methods for signal classification face limitations in dynamic and heterogeneous radio environments, where the coexistence of multiple wireless technologies and the presence of ambient noise pose significant hurdles. To overcome these challenges, the research proposes a novel approach leveraging DL architectures, specifically CNN and VGG16, to automate feature extraction and discern complex signal patterns. By training these DL models on datasets containing 5G NR, LTE, and noise signals, the research seeks to enhance spectrum awareness and classification accuracy. The framework includes a comprehensive evaluation of the proposed DL-based classifiers, considering varying training rates and optimization algorithms, to assess their performance in distinguishing between different signal types. Comparative analysis with traditional signal classification methods will provide insights into the superiority of DL approaches. Furthermore, the research will explore the robustness of the DL classifiers under different noise scenarios and channel impairments, contributing to a deeper understanding of their effectiveness in real-world wireless communication environments. Ultimately, the findings of this research hold significant implications for optimizing spectrum allocation, mitigating interference, and ensuring the seamless coexistence of diverse wireless technologies, thereby advancing the capabilities of future communication systems.

3 Methodology

The section employs deep learning methodologies to enhance spectrum awareness in wireless communications, focusing on the classification of 5G NR, LTE, and noise signals. Two neural network architectures, CNN and VGG16, are presented and thoroughly analyzed for their proficiency in discerning between 5G NR and LTE signals. The methodology involves comprehensive performance evaluations, employing various optimizers, and explores the influence of different training rates on classifier efficacy. The architectures of CNN and VGG16 for classification of 5G NR and LTE signals as follows.

3.1 CNN Architecture

The CNN architecture devised for the classification of LTE, 5G NR, and noise signals employs a hierarchical structure of interconnected layers tailored to extract and learn discriminative features from the input signal data. At its core lies the input layer, which receives the raw signal data in its original format which is in the time-frequency domain (spectrograms). Following this, multiple convolutional layers apply filters or kernels to the input data, systematically scanning for spatial or temporal patterns inherent in the signals. These filters slide across the input data, performing element-wise multiplications and aggregations to highlight relevant features. Each convolutional layer may comprise numerous filters, each dedicated to capturing distinct aspects of the input signals. Activation functions, typically Rectified Linear Units (ReLU), are then applied to introduce non-linearity, enhancing the network's capacity to model complex relationships within the data [11]. Figure 2 represents the proposed CNN for LTE and NR classification.

Subsequent pooling layers serve to down sample the feature maps generated by the convolutional layers, reducing the spatial dimensionality of the data while retaining crucial features. Flattening layers reshape the output of the preceding layers into a one-dimensional vector, preparing it for input into the fully connected layers. These fully connected layers, in turn, process the flattened feature vector to make predictions,

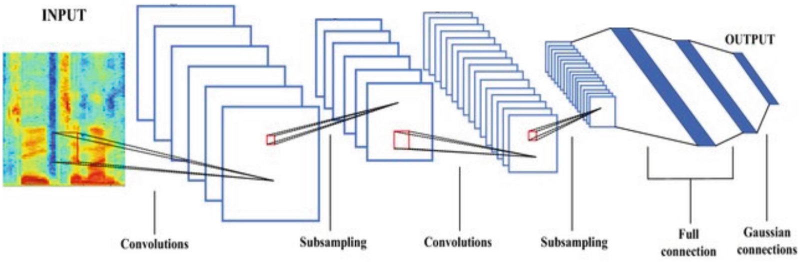

Fig. 2. CNN architecture for signal classification

leveraging their capacity to learn high-level representations of the input data. Each neuron in these layers is intricately connected to every neuron in the preceding layer, facilitating the extraction of intricate signal characteristics. The output layer, typically consisting of three neurons corresponding to LTE, 5G NR, and noise signals, produces the final classification predictions. Activation functions like softmax transform the raw output into probabilities, indicating the likelihood of each class. Throughout training, optimization algorithms such as Adam or stochastic gradient descent with momentum (SGDM) fine-tune the network's parameters to minimize the disparity between predicted and actual labels, ensuring accurate classification of the diverse signal types [12]. Through iterative adjustment of weights and biases via backpropagation and gradient descent, the CNN learns to effectively discern LTE, 5G NR, and noise signals based on the extracted features, thereby enhancing spectrum awareness and classification accuracy in wireless communication systems [13].

3.2 VGG16 Architecture

The VGG16 architecture, renowned for its simplicity and effectiveness, is adapted for the classification of LTE, 5G NR, and noise signals, featuring a deep stack of convolutional layers followed by fully connected layers. The network's structure consists of 16 layers, primarily comprised of convolutional and pooling layers, with relatively small 3x3 convolutional filters [8]. These filters serve to extract intricate spatial features from the input signal data. The architecture's characteristic depth facilitates the learning of complex hierarchical representations, enabling it to discern subtle patterns within the signals. At the outset, the input layer receives the raw signal data, which is subsequently processed by a succession of convolutional layers. These convolutional layers apply multiple 3x3 filters to the input data, systematically scanning for distinctive spatial features. Following each convolutional layer, max-pooling layers down sample the feature maps, reducing their spatial dimensions while preserving essential information [14]. This hierarchical feature extraction process continues through several blocks of convolutional and pooling layers, progressively capturing increasingly abstract representations of the input signals. Figure 3 depicts the VGG16 architecture for signal classification.

After the final convolutional layer, the architecture includes fully connected layers, which integrate the extracted features to make predictions. These layers leverage their

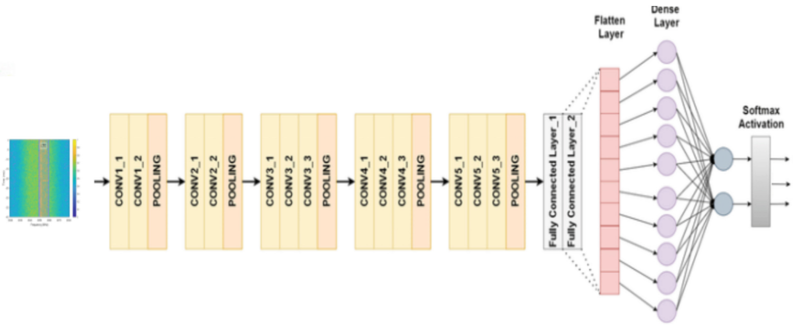

Fig. 3. VGG16 architecture for signal classification

dense connectivity to learn high-level representations of the input data and perform classification based on these representations. Each neuron in the fully connected layers is intricately connected to every neuron in the preceding layer, facilitating the extraction of intricate signal characteristics [15]. The output layer, typically comprising three neurons corresponding to LTE, 5G NR, and noise signals, produces the final classification predictions. Activation functions such as softmax transform the raw output into probabilities, indicating the likelihood of each class [16, 17]. Throughout training, optimization algorithms adjust the network's parameters to minimize the difference between predicted and actual labels, ensuring accurate classification of the diverse signal types. The VGG16 architecture, with its deep and hierarchical design, excels in learning discriminative features from the input signals, contributing to enhanced spectrum awareness and classification accuracy in wireless communication systems [18].

4 Results and Discussions

In simulating the detection of LTE, 5G NR, and noise signals, a comprehensive setup is crucial. Firstly, signals representative of LTE and 5G NR are generated, incorporating varying modulation schemes and frequency allocations to mimic real-world scenarios. These signals are then combined with Additive White Gaussian Noise (AWGN) at different signal-to-noise ratio (SNR) levels ranging from -20 dB to $+ 20$ dB. The AWGN simulates the background noise typically encountered in wireless communication environments. To maintain fidelity, the noise is added to the signal while preserving its characteristics and ensuring a realistic representation of noisy channel conditions. The simulation strategy involves iteratively testing the performance of detection algorithms across the range of SNR levels, evaluating factors such as detection accuracy and robustness. This comprehensive approach allows for the assessment of algorithm efficacy under varying noise conditions, providing insights into the algorithm's reliability in real-world noisy environments.

In preparing signals for deep learning-based classification, the Short-Time Fourier Transform (STFT) emerges as a pivotal technique for converting temporal signals into time-frequency spectrograms, facilitating their representation as image inputs. Initially, the signal undergoes segmentation into shorter frames, enabling localized analysis of its frequency content over time. Each segmented frame is then windowed using functions like Hamming or Hanning to mitigate spectral leakage. The STFT is subsequently computed for each frame, yielding a time-frequency representation wherein the Fourier Transform is computed for discrete time segments. This results in a spectrogram, where time is depicted along the horizontal axis and frequency along the vertical, with pixel intensity indicating the magnitude or power of frequency components at specific intervals. Treating the spectrogram as an image, with each pixel representing spectral information at a particular time, enables the utilization of CNN, VGG16 for signal classification. By leveraging the strengths of both signal processing and image analysis, this approach empowers deep learning models to discern intricate temporal and spectral patterns inherent in signals, thereby enhancing their capability to classify LTE, 5G NR, and noise signals accurately.

Table 1 represents the confusion matrix of CNN classifier at three different training rates and with three different optimizers. Similarly Table 2 depicts the performance of VGG16. Table 3 shows the training and testing performance of VGG16 and CNN classifiers. From the simulations it is observed that VGG16 outperforms the CNN classifiers with different optimizers. Among three different optimizers RMSProp outperforms followed by ADAM and SGDM optimizers. The maximum accuracy achieved by VGG16 classifier is 91.7% and CNN is 92.8% respectively. However, from the simulations it is crucial to note that the choice of optimizer plays a significant role, with RMSProp exhibiting the highest performance, followed by ADAM and SGDM.

Table 1. Confusion Matrix of CNN

Optimizer	Class/ Signal	Training Rate (%)								
		90			80			70		
		LTE	Noise	NR	LTE	Noise	NR	LTE	Noise	NR
ADAM	LTE	94	3	0	194	5	6	263	6	4
	Noise	2	86	9	2	176	7	10	244	11
	NR	4	11	91	4	19	187	26	50	285
SGDM	LTE	67	4	8	188	51	55	251	55	79
	Noise	3	66	5	0	111	1	38	209	52
	NR	30	30	87	12	38	144	10	36	169
RMSProp	LTE	97	4	7	178	3	1	285	20	26
	Noise	1	84	8	8	142	7	8	244	39
	NR	2	15	85	14	55	192	6	36	235

Through the wide range of simulations and hyperparameter tuning this paper not only contributes to the advancement of spectrum management but also provides practical implications for real-world implementations in wireless communication systems. The findings affirm the potential of deep learning architectures in optimizing network performance, mitigating interference, and fostering the seamless integration of IoT devices,

Table 2. Confusion Matrix of VGG16

Optimizer	Class/ Signal	Training Rate (%)								
		90			80			70		
		LTE	Noise	NR	LTE	Noise	NR	LTE	Noise	NR
ADAM	LTE	91	3	3	185	9	5	278	6	13
	Noise	5	85	10	5	165	26	8	263	33
	NR	4	12	87	10	26	169	13	31	254
SGDM	LTE	89	2	4	176	4	2	280	24	32
	Noise	9	92	23	2	140	5	5	225	24
	NR	2	6	73	22	56	193	14	51	244
RMSProp	LTE	95	4	3	173	2	3	276	13	8
	Noise	2	95	9	12	157	17	11	251	28
	NR	3	4	88	15	41	180	12	36	264

Table 3. Performance Comparision of CNN and VGG16

DL Model	Optimizer	Validation Accuracy (%)			Test Accuracy (%)		
		90	80	70	90	80	70
CNN	ADAM	87.8	87.9	88.1	90.3	92.8	88.1
	SGDM	73.7	71.7	72.9	73.3	73.8	70
	RMSProp	87.1	87.1	86.7	87.7	85.3	85.0
VGG16	ADAM	85.9	90.4	88.6	87.7	86.5	88.4
	SGDM	81.1	82.5	89.5	84.7	84.8	83.3
	RMSProp	91.1	86.7	91.4	91.7	85.0	88.0

thereby bolstering communication efficiency and reliability in the era of diverse wireless technologies.

5 Conclusion

This paper presents the critical role of deep learning architectures for spectrum sensing in the context of evolving wireless communication landscapes, specifically focusing on the coexistence of 5G, LTE, and noise signals. The deployment of deep learning architectures, CNN and VGG16, has proven instrumental in automating the classification process, thereby significantly enhancing spectrum awareness within cellular systems. The comparative analysis between CNN and VGG16 reveals compelling insights into their respective performances. Particularly, VGG16 appears as the more proficient classifier, demonstrating its superiority in accurately discerning 5G NR and LTE signals. The nuanced exploration of different optimizers—RMSProp, ADAM, and SGDM—offers valuable considerations for optimizing the deep neural networks' efficiency. The observed maximum accuracies of 91.7% for VGG16 and 92.8% for CNN showcase the effectiveness of these models in distinguishing between diverse wireless signals. Future research could explore real-world deployment scenarios, considering dynamic and complex wireless environments. Integration of advanced deep learning techniques, such as recurrent neural networks, could further enhance spectrum sensing capabilities for evolving communication technologies.

References

1. Huynh-The, T., Pham, Q.-V., Nguyen, T.-V., da Costa, D.B., Kim, D.-S.: Racomnet: high-performance deep network for waveform recognition in coexistence radar-communication systems. In: 2022 IEEE International Conference on Communications (ICC), pp. 1–6 (2022). https://doi.org/10.1109/ICC.2022.9781658
2. Pham, Q.-V., Nguyen, N.T., Huynh-The, T., Le, L.B., Lee, K., Hwang, W.-J.: Intelligent radio signal processing: a survey. IEEE Access **9**, 83818–83850 (2021). https://doi.org/10.1109/ACCESS.2021.3066589
3. Gao, J., Yi, X., Zhong, C., Chen, X., Zhang, Z.: Deep learning for spectrum sensing. IEEE Wireless Communications Letters **8**(6), 1727–1730 (2019). https://doi.org/10.1109/LWC.2019.2937971
4. Venkata Subbarao, M., Samundiswary, P.: Performance analysis of modulation recognition in multipath fading channels using pattern recognition classifiers. Wireless Pers. Commun. **115**, 129–151 (2020). https://doi.org/10.1007/s11277-020-07564-z
5. Venkata Subbarao, M., Keerthana, B., Ramesh Varma, D., Terlapu, S.K., Challa Ram, G.: Automatic modulation classification under AWGN and fading channels using convolutional neural network. In: Chakravarthy, V., Bhateja, V., Flores Fuentes, W., Anguera, J., Vasavi, K.P. (eds.) Advances in Signal Processing, Embedded Systems and IoT. Lecture Notes in Electrical Engineering, vol. 992, Springer, Singapore (2023). https://doi.org/10.1007/978-981-19-8865-3_20
6. Venkata Subbarao, M., Samundiswary, P.: Spectrum sensing in cognitive radio networks using time–frequency analysis and modulation recognition. In: Anguera, J., Satapathy, S., Bhateja, V., Sunitha, K. (eds.) Microelectronics, Electromagnetics and Telecommunications. Lecture Notes in Electrical Engineering, vol. 471, Springer, Singapore (2018). https://doi.org/10.1007/978-981-10-7329-8_85
7. Huynh-The, T., Pham, Q.-V., Vu, T.-H., da Costa, D.B., Hoang, V.-P.: Intelligent spectrum sensing with convnet for 5G and LTE signals identification. In: 2023 IEEE Statistical Signal Processing Workshop (SSP), pp. 140–144, Hanoi, Vietnam (2023)
8. Alhazmi, M.H., Alymani, M., Alhazmi, H., Almarhabi, A., Samarkandi, A., Yao, Y.-D.: 5G signal identification using deep learning. In: 2020 29th Wireless and Optical Communications Conference (WOCC), pp. 1–5, Newark, NJ, USA (2020). https://doi.org/10.1109/WOCC48579.2020.9114912
9. Reddy, M.M.K., Monisha, M.: Enhanced deep learning architectures for spectrum sensing in cellular networks. In: 2023 8th International Conference on Communication and Electronics Systems (ICCES), pp. 1285–1290, Coimbatore, India (2023). https://doi.org/10.1109/ICCES57224.2023.10192889

10. Biswas, A., Gupta, V.R.: Multiband antenna design for smartphone covering 2G, 3G, 4G and 5G NR frequencies. In: 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), pp. 84–87, Tirunelveli, India (2019). https://doi.org/10.1109/ICOEI.2019.8862713
11. Ram, G.C., Venkata Subbarao, M., Ramesh Varma, D., Krishna, A.S.: Enhanced deep convolutional neural network for identifying and classification of silicon wafer faults in IC fabrication industries. In: 2023 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), pp. 1–6, Chennai, India (2023). https://doi.org/10.1109/WiSPNET57748.2023.10133996
12. Venkata Subbarao, M., Sindhu, J.T.S., Harshitha, N.N.S., Vasavi, K.P., Krishna, A.S., Ram, G.C.: Detection of retinal degeneration via high-resolution fundus images using deep neural networks. In: 2023 Second International Conference on Electronics and Renewable Systems (ICEARS), pp. 955–960, Tuticorin, India (2023). https://doi.org/10.1109/ICEARS56392.2023.10085273
13. Xie, J., Fang, J., Liu, C., Li, X.: Deep learning-based spectrum sensing in cognitive radio: a CNN-LSTM approach. IEEE Commun. Lett. **24**(10), 2196–2200 (2020). https://doi.org/10.1109/LCOMM.2020.3018194
14. Zhang, R., Lim, T.J., Liang, Y., Zeng, Y.: Multi-antenna based spectrum sensing for cognitive radios: a glrt approach. IEEE Trans. Commun. **58**(1), 84–88 (2010). https://doi.org/10.1109/TCOMM.2009.12.080594
15. Nalli, P.K., Venkata Subbarao, M., Garapati, D.P., Priyakanth, R., Kumar, G.P.: Performance analysis of pre-trained deep learning architectures for classification of corn leaf diseases. In: 2023 International Conference on Network, Multimedia and Information Technology (NMITCON), pp. 1–8, Bengaluru, India (2023). https://doi.org/10.1109/NMITCON58196.2023.10275915
16. KrishnaKishore, K., VenkataSuman, J., Madhavi, M., Hema, M., Venkataramana, G.: Scrambled UFMC and OFDM techniques with APSK modulation in 5G networks using particle swarm optimization. IEEE Access. (2024). https://doi.org/10.1109/ACCESS.2024.3421311.
17. Kishore, K.K., Rajasekaran, A.S., Keshta, I., et al.: Intelligent dynamic spectrum access using fuzzy logic in cognitive radio networks. Discov Appl Sci **6**, 18 (2024). https://doi.org/10.1007/s42452-024-05641-7
18. Krishna Kishore, K., Sri, D.K., Naveen, J., et al.: Performance evaluation of universal filter multi carrier (UFMC) and orthogonal frequency division multiplexing (OFDM) with amplitude phase shift keying (APSK) modulation. PREPRINT (Version 1) available at Research Square (2023). https://doi.org/10.21203/rs.3.rs-3155601/v1