ISSN: 2710-2165

Deep Learning-based Signal Identification in Wireless Communication Systems: A Comparative Analysis on 3G, LTE, and 5G Standards

Alaa Hussein Abdulaal[*], Nooruldeen Haider Dheyaa[**], Ali H. Abdulwahhab[***], Riyam Ali Yassin[****], Morteza Valizadeh[*****], Baraa M. Albaker[******], Ammar Saad Mustaf[*******]

[*] Department of Electrical Engineering, Al-Iraqia University
[*]Department of Electrical Engineering, Urmia University
Engineeralaahussein@gmail.com
https://orcid.org/0000-0003-2316-2822

[**] Department of Communication Engineering, Kashan University
noor.h6161@gmail.com
https://orcid.org/0009-0002-4295-135X

[***]Department of Electrical and Computer Engineering, Altinbas University
ahabdulwahhab@gmail.com
https://orcid.org/0000-0001-6041-5185

[****]Department of Electrical Engineering, Urmia University
RiyamAliYassin@gmail.com
https://orcid.org/0009-0004-1202-0380

[*****] Department of Electrical Engineering, Urmia University
m.valizade@gmail.com
https://orcid.org/0000-0003-2204-3303

[******] Department of Electrical Engineering, Al-Iraqia University
baraamalbaker@ymail.com
https://orcid.org/0000-0002-6030-3121

[*******] Department of Missions and Cultural Relations, Al-Iraqia University
marsd1481@gmail.com
https://orcid.org/0009-0000-7346-0305

Abstract

Efficient signal identification in wireless communication systems is critical for optimal service provision. However, the complexity of contemporary criteria and factors such as noise and fading make it hard to do so. To address this problem, convolutional neural networks (CNNs) are used to classify signals using 3G, LTE, and 5G standards. This approach involves creating a range of datasets with different Signal-to-Noise Ratios (SNR) and introducing Rayleigh fading to represent real-world environments. Two CNN architectures for dependable assessment, VGG19 and ResNet18, with robust 5-fold cross-validation, are employed. To test model resilience, the dataset includes Poisson noise and Thermal noise. Despite noise and fading in the system, VGG19 and ResNet18 show high accuracies across all standards. However, ResNet18 demonstrates relatively better performance, especially under Poisson noise conditions. Both models also have good signal detection from among noises generated by Poisson thermal or Rayleigh distribution. ResNet18 demonstrates a commendable average accuracy of 99.52%, while VGG19 Net demonstrates 97.14%. CNNs effectively identify signals amidst noise scenarios and contribute to advancing deep learning techniques in signal processing, enhancing the reliability of wireless communication systems.

Keywords- Signal ID, Wireless Communication, Deep Learning, 5G, CNN.

I. Introduction

The revolution of the telecommunication industry started with the emergence of 5G technology, which promises to transform connectivity and drive innovation across many industries worldwide. The probable uses of 5G are numerous and different in purpose, ranging from enabling ultra-fast mobile communication services to transforming healthcare delivery through eHealth implementations. In mobile telecommunications, for instance, 5G networks present much higher data rates, hence lower latency than their predecessors, allowing for seamless multimedia streaming, HD video calls, and immersive virtual reality experiences [1]. Also, remote patient monitoring, telemedicine services, and AR-assisted surgeries could be transformed by deploying 5G infrastructure, improving access to care delivery and patient outcomes [2]. One main feature that allows for 5G technology is the usage of the radio frequency spectrum made up of three main bands: Low-Band, Mid-Band, and High-Band. Below this frequency threshold, the operation occurs in the Low-Band spectrum, which gives extensive coverage plus penetration, thus suitable for wide-area connectivity. The Mid-Band spectrum is 3.6 GHz to 6 GHz, making a trade-off between coverage and capacity, offering higher data rates and reduced latency than Low-Band frequencies. Contrariwise, the High-Band spectrum ranges from 24 GHz to 40 GHz, making it possible to transmit much data quickly. Still, due to its limited coverage area (prone to signal fading), it requires denser network deployment [3,4]. Effective identification methods must be implemented to manage radio resources efficiently in the telecommunications industry's transition from previous cellular technologies such as UMTS (3G) and LTE (4G) towards 5G. Recently, deep learning has gained prominence as a significant technology in signal identification by offering automatic extraction techniques that are useful in separating different signals within the ecosystem of 5th-generation mobile communication [5]. Deep learning algorithms using Automatic Signal Identification (ASI) can analyze and classify signals across domains such as image classification, automatic speech recognition, or spectrum surveillance with exceptional accuracy [6].

Additionally, deep learning algorithms have high degrees of adaptability that enable them to learn and classify signals in real-time, thus improving the efficiency and reliability of 5G networks [7]. Several methods are commonly used to classify signals, among them being Likelihood-based and Feature-Based approaches, which exploit techniques such as Pilot Induced Cyclostationary (PIC) and Gaussian Maximum Likelihood (GML) [8]. These use statistical properties and signal attributes to quickly identify the same, thus enabling spectrum surveillance in dynamic environments of cognitive radio operations [9]. Despite their usefulness in mastering matched filters and processing time-domain IQ data, Convolutional Neural Network (CNN) models encounter specific difficulties, mostly with unknown sampling rates [10]. To this end, O'Shea and West have delved into CNN architecture subtleties, such as how layer sizes and depths affect classification accuracy [11]. More importantly, they have developed novel complex inception modules combining CNNs with Long Short-Term Memory (LSTM) networks for better performance, thereby advancing state-of-the-art signal identification approaches [12]. In parallel with this, recent research has focused on applying deep learning techniques for GSM, UMTS, and LTE signal recognition, highlighting spectrum awareness and customizing algorithms to accommodate different characteristics of each cellular system [13]. With this foundation, the integration of Massive MIMO (Multiple-Input Multiple-Output) techniques in next-generation wireless systems looks forward to further enhancing the capabilities of 5G networks, resulting in unprecedented spectral efficiency and connectivity [14].

Additionally, details from Representation Learning and Receiver Design methods allow 5G networks to be improved so that communication systems can attain robustness and reliability [14]. Similarly, the development, including Cognitive Radio Spectrum Access within Sequential Neural Networks and emerging security paradigms around Machine Learning in IoT systems, underpin the interdisciplinary nature of 5G technology and necessitate comprehensive approaches to mitigate emerging challenges. As the field evolves further, deep learning has merged with signal processing and wireless communications, coming up with even more tremendous promise for realizing the full potential of 5G networks by ushering into an era of connectivity and innovation.

This paper aims to use deep learning, particularly convolutional neural networks (CNNs), to identify signals using different wireless communication standards such as 3G, LTE, and 5G. Herein, the process incorporates creating a dataset of random signals represented as images, each having different signal-to-noise ratio (SNR) levels for every class. Each standard is produced using appropriate functions, and real-world channel conditions are mimicked using Rayleigh fading effects. Lastly, the data set will be partitioned into training, validation, and testing subsets for model evaluation. The CNN model design consists of convolutional and pooling layers followed by flattening and fully connected layers and ending with a SoftMax classifier. This model aims to use CNN's abilities for automatic feature extraction to identify signals across various wireless communication standards precisely.

II. 3G, LTE, AND 5G SIGNALS

The next part is the exposition of three types of signals, namely, 3G, LTE, and 5G, with a discussion of their attributes. The research methodology comprises two phases designed to address the study's objectives. Signals are initially generated within various environments, including signal types, signal-to-noise ratio levels, fading phenomena, and dataset sizes. This multi-pronged strategy ensures that the database can withstand different conditions and can, therefore, shed light on how signals behave in varied environments. Subsequently, deep learning algorithms are employed precisely and rigorously to identify the signal types an abstract or digital signal uses. With the abundance inherent in this well-crafted data set, fine-grained differences and patterns among different classes of signals are detected, hence providing accurate and reliable support for identification. It is hoped that comprehensive insights into signal identification across different wireless communication standards will be provided through a carefully designed methodology.

A. UMTS (3G)

The UMTS frequency bands are the radio waves mainly used for data transmission in third-generation (3G) wireless Universal Mobile Telecommunications System (UMTS) networks. These spectra range from 850 to 1900 MHz, facilitating comprehensive area coverage and effective communications [11]. The UMTS frame structure provides a basic configuration for organizing data transmission in the system.[15] More specifically, the super frames that make up the UMTS frame structures comprise seventy-two frames, which are higher-level organizational units.[16] However, each frame is divided into fifteen slots that form the smallest unit of transmitting data. These bits or symbols are divided into 2560 chips per slot, thus providing resolution for signal processing and modulation [16]. On the contrary, this results in accurate scheduling and coordination between transmissions and receptions, hence leading to idealizing the use of available bandwidths and spectrum resources. This information has a time-keeping function where its understanding will support rightness during information sending via 3G networks. Time is broken down into discrete intervals of 10 milliseconds by the system to segment it into different intervals for data exchange, thereby making communication between network nodes and mobile devices reliable and efficient. Moreover, each slot lasts for only 0.667ms, the lowest duration possible when transmitting packets over radio frequency channels that enable quick response communication services. To devise and optimize 3G network protocols, algorithms, and devices, the intricacies of the UMTS frame structure have to be grasped, as shown in Figure 1. Operators can manage their network resources optimally by using the temporal arrangement of the frame structure, thus decreasing interference and improving the overall quality of service for subscribers.

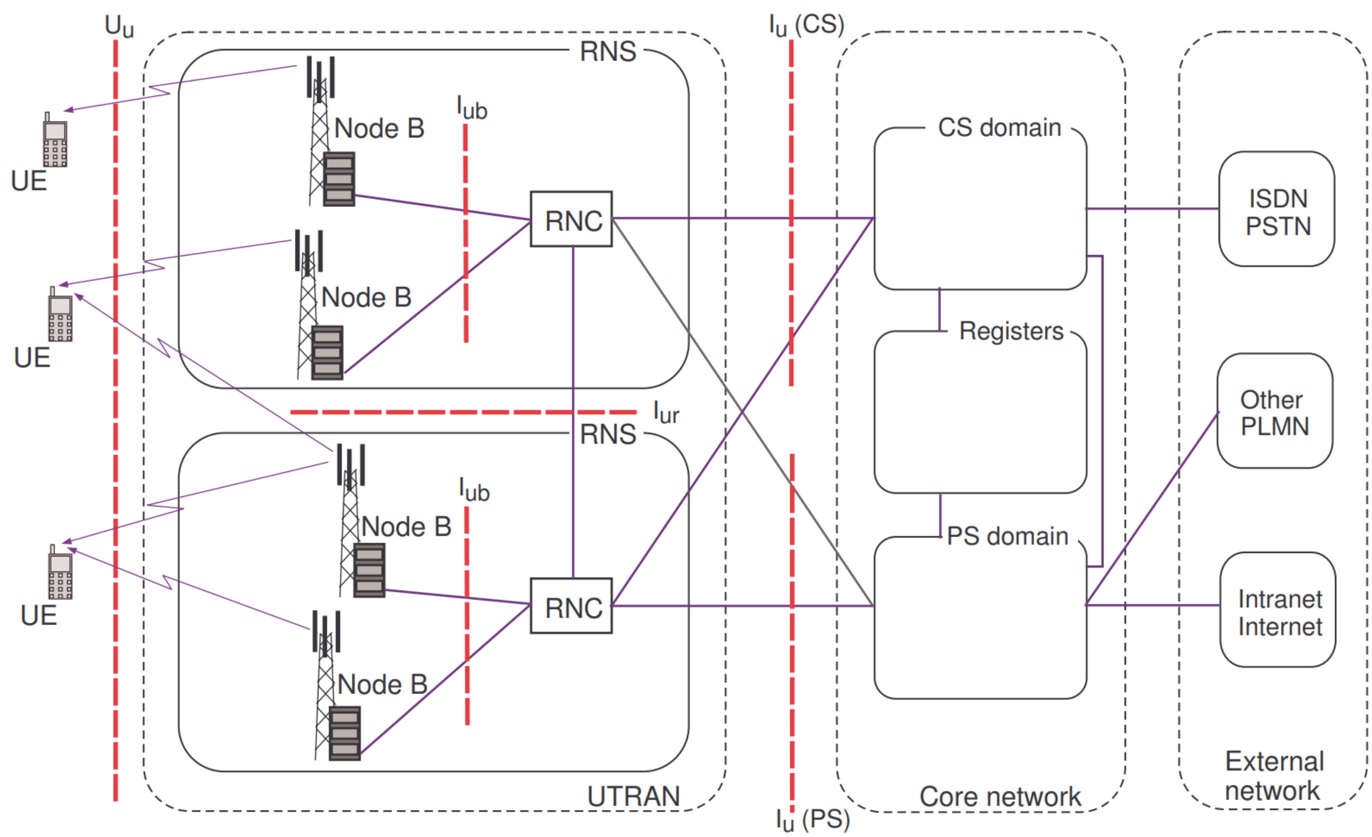

Figure 1. UMTS (3G) Frame [17]

B. LTE

LTE mobile networks use a frequency of 700MHz and 2600 MHz for efficient data transmission [18]. Thus, one of the most essential things in this network architecture is the frame structure illustrated in Figure 2. In other words, an LTE frame contains ten millisecond-long frames that are partitioned into two sub-frames. Consequently, data transmission will be organized at each frame level for efficient communication between network elements and user devices. More so, this facilitates accurate scheduling and synchronization of transmissions, which results in improved network performance and resource utilization [19]. To go further into detail, different sections within the LTE frame structure segregate time intervals allocated to data transmission from those for control signaling, thus enabling effective management of resources during network activities. However, breaking the frames into subframes allows adaptability to different traffic patterns, translating into dynamic resource allocation and higher quality of service levels for the final consumers. In addition, a Long-Term Evolution (LTE) network with a 10-millisecond time frame tries to support modern communication systems that balance efficient data transfer and low latency rates. This ensures temporal uniformity to meet the requirements of various services and applications [20]. The details of the LTE frame structure are critical regarding network architecture, optimization exercises, and performance evaluations. These were designed on time-based structuring so operators can optimize network resources, mitigating interference and improving user experience. This understanding allows one to adapt quickly as traffic patterns change, efficiently allocate resources, and manage networks dynamically. Thus, knowledge of LTE frame structure enables fine-tuning operational parameters, resulting in optimal network performance and enhanced user satisfaction.

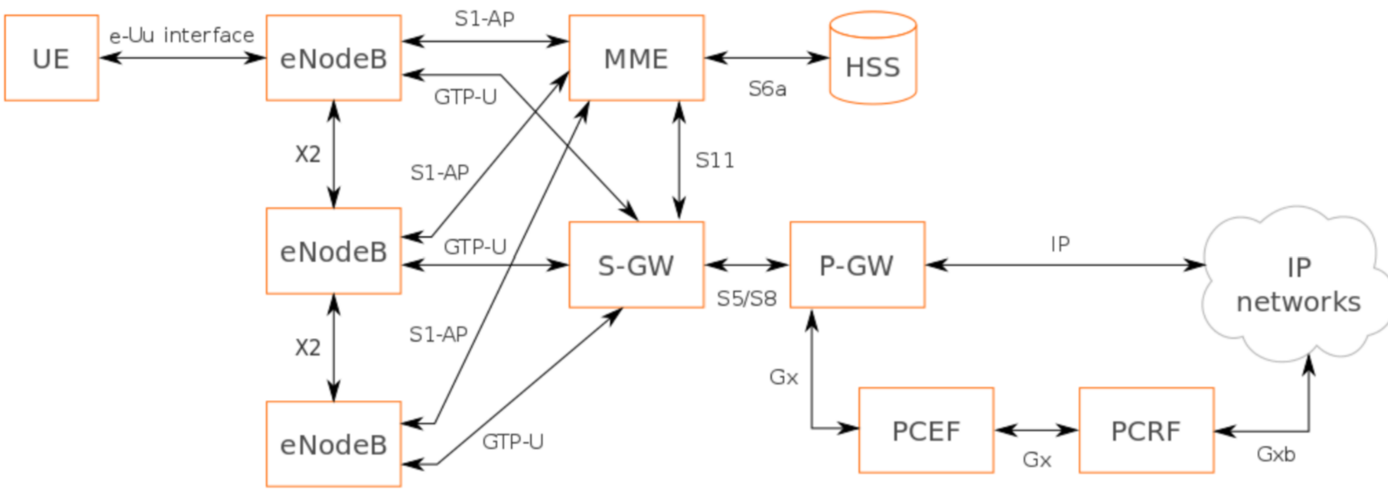

Figure 2. LTE Frame

C. 5G

In the frame structure of a 5G signal illustrated in Figure 3, the duration is ten milliseconds, divided into ten subframes, each lasting for one millisecond by LTE [21]. There are two slots within these subframes, each containing fourteen OFDM symbols. Notably, whereas LTE only supports one subcarrier spacing of 15 kHz, this constraint does not hold within 5G NR, making it possible to have multiple types of subcarrier spacing [22]. This feature is critical as it will allow for flexibility on what frequency spacing can be used across various spectrum bands in 5G. Regarding spectrum usage, the networks mentioned above use spectrum from 600 MHz to 6 GHz (already employed in established LTE networks) and tap into millimeter wave bands ranging from 24 GHz to 86 GHz [3]. The distribution of these frequencies among different services significantly shapes some characteristics associated with fifth-generation mobile technology. For example, maximum bandwidth varies depending on the utilized frequency range, and so does subcarrier spacing. In other words, within a sub-6 GHz band, a fifth-generation network's maximum bandwidth can span up to a hundred megahertz [23].

On the contrary, this bandwidth equals four hundred megahertz in the case with a millimeter wave range [24]. Furthermore, selecting such frequencies directly affects how well these systems work and what they can do. All urban and sub-urban areas may have reliable connections if one uses frequency bands at lower frequencies within the range of sub-six gigahertz due to broader coverage provided and better penetrability through obstacles. However, millimeter waves are better regarding data rates, although they suffer from absorptions in the atmosphere and blockages to a greater extent than any other. Consequently, this calls for denser network deployments and line-of-sight propagation for optimum performance [19]. Also, 5G New Radio has different subcarrier spacings which help in the effective use of spectrum while supporting various services with specific requirements such as enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC) [23]. Such flexibility in service delivery makes it possible for operators to customize their networks to suit the specific needs that improve quality of service within the network, leading to better user experiences through resource optimization.

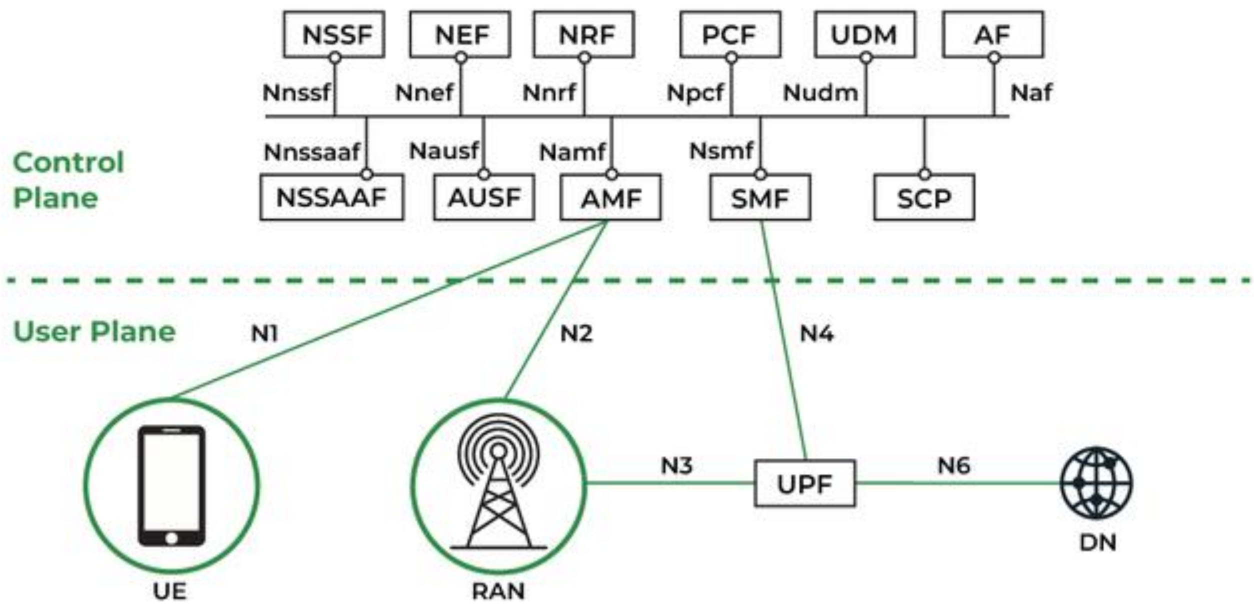

Figure 3. 5G Frame

III. SIGNAL IDENTIFICATION USING DEEP LEARNING

Deep learning is a mighty array of algorithms that assists in object categories like computer vision and image recognition. One of these is turning raw data into images and scrutinizing them using Convolutional Neural Networks (CNN). This section sampled a variation of signals for each modulation type at different SNRs, and the methodology was presented. Moreover, it explains the architecture and training process of CNN models referred to as VGG 19 [25] and ResNet 18 [26], explicitly designed for classification tasks. Notably, a reliable experimental setup incorporating five-fold cross-validation is provided, allowing for the robustness and generalizability of the model over various deep-learning parameter settings. The considered signals include those transmitted in 3G, LTE, and 5G networks, thereby making it possible to comprehensively evaluate the efficacy of the proposed approach across multiple generations of wireless communication technologies. As a bonus, comprehensive information regarding the preprocessing actions taken to make raw signals suitable for input into CNN models is also given, thereby boosting the visibility and repeatability of our research techniques.

A. Generating Signals

The dataset produced in this experimental configuration had 1000 different two-dimensional signals as a beginning point for feature extraction methods. Diverse approaches are used to ensure that the signal variations of various generations of mobile communication technologies are comprehensive by using UMTS features of MATLAB for creating 3G signals, the "LTE RMCDL" function library for producing 4G signals, and the toolbox of 5G signal generation. This approach aims to capture the specificities of every technology applied while covering a wide range of wireless standards. The dataset contained various signals with SNRs ranging from -20 dB to 20 dB, thus allowing it to imitate real-world noise disturbances. Moreover, the dynamic fading phenomena are reproduced by introducing Rayleigh effects into the signals to improve their realistic nature in the database. Also incorporated within these devices were two types of stochastic noise sources – Poisson and Thermal Noise – which introduced random interference into the signals, enhancing the data set's diversity. All signal types were kept with the same 15 kHz subcarrier spacing throughout to ensure and facilitate effective integration into standard communication protocols.

Moreover, industry standards are being met using Orthogonal Frequency Division Multiplexing (OFDM) modulation with only one subframe to promote interoperability. Every signal type in the dataset had a frame length of 10 milliseconds, providing temporal coherence and facilitating compatibility across datasets. The dataset was carefully split for robust model training, testing, and validation. The training set had 80% of the samples, and the testing set had the remaining 20% using 5-fold cross-validation to avoid overfitting, which may affect the reliability and generalizability of subsequent analyses, thus showing the commitment to methodological rigor.

B. Data Processing

Through the realization of Additive White Gaussian Noise (AWGN) channel simulation over noise levels that range from -20 dB to 20 dB, the resulting noisy signals are combined for training and testing Convolutional Neural Network (CNN) models: VGG19 and

ResNet18 [25-26]. Later, this kind of signal is integrated with Rayleigh fading effects to enhance complexity before re-iterating the above procedures for training and testing. When evaluating identification performance, image representations are adopted as a benchmark. To begin with, each time-domain signal is transformed into a JPG image format having dimensions of 128 × 128 pixels. Also, they have been sampled into two-dimensional vectors, each having 307,200 components, which were then stored in CSV files for further analysis later on. Both CNN model architectures are equipped with two-dimensional convolutional layers since processing through image representations is required here.
Moreover, modeling efficiency is achieved using only real parts of the time domain signals. Signal features are analyzed by re-sampling at various distributed points such as 1000, 5000, and 10000. Through this process, the characteristics of signals are considered in terms of identification performance. The described method of data processing recognizes the complexity of the wireless communication environment. It covers various scenarios seen in practical applications, making the identification model adaptable and robust enough for the real world. Using image representations and careful feature extraction, VGG 19 and ResNet18 CNN models can appropriately detect patterns amidst noise with fading, thus showing their suitability in signal identification tasks.

C. Deep learning models

In CNN models' development, VGG19 and ResNet18 architectures are selected for the well-acknowledged performance of image classification tasks (signal identification objectives). VGG19 [25] has stacked convolutional layers followed by max-pooling operations that enable hierarchical feature extraction. This leads to fully connected layers and a SoftMax classifier for dividing signals into 3G, LTE, or 5G, as shown in Figure 4. On the contrary, ResNet18 [26] uses residual connections to train deeper networks, which help overcome the vanishing gradient problem, hence improving the model, as shown in Figure 5. Both architectures use convolutional layers and max-pooling operations to effectively reduce input signals' dimensions. As a result, these tensors from the third max-pooling layer change from 4-dimensions to 2-dimensions for convenience in subsequent processing stages. Inside VGG19 architecture are three fully connected layers, each with 4096 neurons, followed by one-layer of 1000 neurons representing ImageNet dataset classes activated with rectified linear units (ReLU) [27-28]. ResNet18 has a fully connected layer with 512 neurons preceding the output layer and also has ReLU's activation functions. The last classification step involves using the SoftMax function to determine which category each input signal belongs to [27]. To measure the performance of these models reliably, 5-fold cross-validation is used where the dataset is divided into five equal parts, rotated among each fold as a validation set for reliable estimates of how well models performed on different subsets of data aimed at enhancing the credibility of the signal identification models [27], [29]. It is worth noting that this selection was motivated by their efficiency in handling image data, which is crucial in complex wireless communication environments.
Moreover, they are designed as feed-forward artificial neural networks, which are efficient for image recognition and classification needs. These models are created using Python 3.7 through the Google TensorFlow library, which enables effective computation inside the Jupyter Notebook environment. Sixteen convolutional layers were present in the VGG19 model, followed by three fully connected layers. ReLU activation functions were used in this network with an output classification of 3 classes (3G, LTE, 5G). The final layer had 1000 neurons adapted for ImageNet classes and employed a SoftMax cross-entropy loss function. The training was done using the Adam optimizer at a learning rate of 0.001. The model involved fifty epochs of training and had a batch size of thirty-two.
Conversely, ResNet18 featured eighteen convolutional layers and one fully connected layer. Like VGG19, it is classified into three subfields (3G, LTE, and 5G) and implements ReLU activation characteristics in its outputs. Also, the model's loss function was SoftMax cross-entropy.

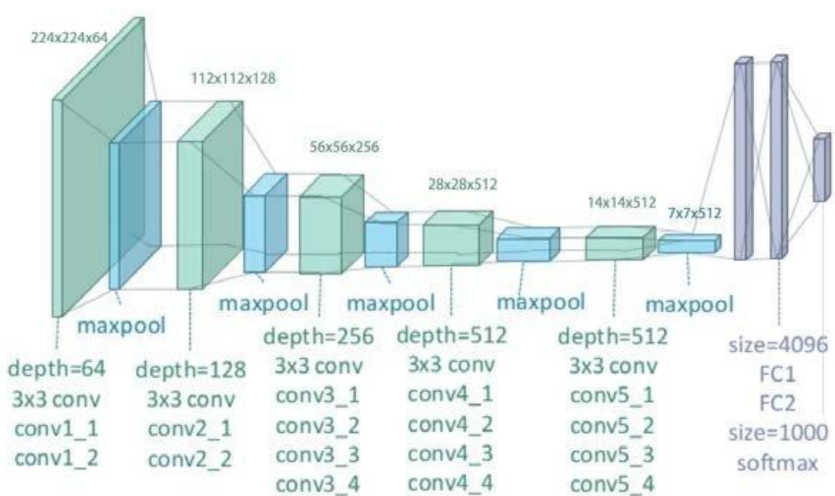

Figure 4. VGG19 Architecture [27]

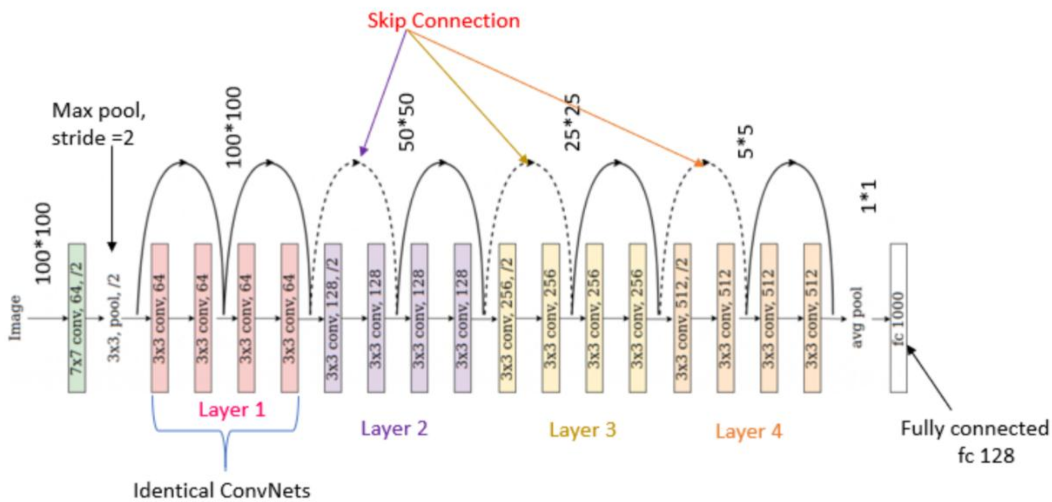

Figure 5. ResNet18 Architecture [27]

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The results of this experimental study investigated signal identification using two different convolutional neural network (CNN) architectures: VGG 19 and ResNet 18. The rigorous application of 5-fold Cross-validation enables robustness assessment in different experimental environments. The main emphasis of this work is the deliberate introduction of white noise into data sets containing various strengths. This manipulation tests the CNN models' robustness over signal-to-noise ratio (SNR) settings. Additionally, it systematically investigated how dataset size and feature combination affect model performance indicators such as classification accuracy, sensitivity, specificity, precision, and F1 score [27-30].
Furthermore, the fading in channels on CNN's ability will be investigated to classify signals accurately. In this regard, the results regarding adaptation and efficiency of CNN architecture in real-world signal propagation conditions have been analyzed exhaustively to be useful in other applications involving CNNs in signal identification domains. These findings significantly expand the understanding and practical uses of CNNS for field signals.

$$\mathrm{Accuracy} = (\mathrm{tp} + \mathrm{tn})/\mathrm{total\ samples} \tag{1}$$

$$\mathrm{Sensitivity} = \mathrm{tp}/(\mathrm{tp} + \mathrm{fn}) \tag{2}$$

$$\mathrm{Specificity} = \mathrm{tn}/(\mathrm{tn} + \mathrm{fp}) \tag{3}$$

$$\mathrm{Precision} = \mathrm{tp}/(\mathrm{tp} + \mathrm{fp}) \tag{4}$$

$$\mathrm{F1\ score} = 2 * (\mathrm{precision} * \mathrm{sensitivity}) / (\mathrm{precision} + \mathrm{sensitivity}) \tag{5}$$

In Table I, the image generation distribution of signals is presented for each wave type, and this was done by categorizing them into two categories – Poisson noise and Thermal noise. Across UMTS, LTE, and 5G NR waveforms, an equivalent number of generating signal images for both kinds of noise totals 350. By doing this, it becomes possible to have a balanced distribution that can comprehensively evaluate CNN models' performance across various signal characteristics and noise conditions.

TABLE I. DISTRIBUTION GENERATING OF WAVEFORMS

Type	UMTS Waveform	LTE Waveform	5G NR Waveform
Poisson Noise	350	350	350
Thermal Noise	350	350	350

Table II provides the evaluation results and insights into the abilities of VGG19 Net and ResNet18 in distinguishing signals from noises under various noisy environments. VGG19 Net demonstrates commendable accuracy across several sub-classes under Poisson noise with rates such as 92.86%, 97.14%, and 95.71%, respectively, for UMTS, LTE, and 5G NR waveforms. This suggests that most types or varieties of signals obtained from different sources, including standards, can be correctly classified by the network even when random fluctuations are present in intensity due to the Poisson effect being affected so much". Moreover, this VGG19 Net has significantly improved its accuracy levels at thermal noise points where it has achieved accuracy levels between 95.71%,97.14%, and 98.57% for UMTS, LTE &5G NR waveforms, respectively". This implies that VGG19 Net is more resistant to Thermal noise due to the random movement of electrons within the circuit, which affects signal strength and frequency. The model exhibits strong sensitivity by having many true positive signals in all sub-classes and noise types. In particular, sensitivity ranges from 94.44% to 98.53% under Poisson noise and 95.83% to 98.57% under Thermal noise. This denotes that VGG19 Net can successfully detect the presence of signals from its intended source while ignoring them where there are noises.

Additionally, specificity values for VGG19 Net remain consistently high, reflecting its ability to identify true negative signals accurately. Scores range from 96.48% to 99.28% under Poisson noise and 97.89% to 99.28% under Thermal noise conditions on this network's specificity values only indicate high false alarm rates because they cannot distinguish between absence of signal from the desired source due to contamination by noises or other reasons such as low SNR caused by channels fading ResNet18, on the other hand, demonstrates excellent accuracy across various subclasses in terms of average accuracy rate amounting at about 98.57%. Notably, UMTS and 5G NR waveforms have perfect accuracy scores of 100%. This shows that irrespective of variations in Poisson noise levels, ResNet18 can always classify these two types/standards of signals perfectly. Even though there is thermal noise, ResNet18 still attains a high level of accuracy, with the UMTS waveform having 100% and 98.57% concerning LTE and 5G NR waveforms, respectively. This implies that ResNet18 is also resistant to Thermal noise, particularly on UMTS waveform, which got the highest score again. Sensitivity measures for ResNet18 correspond to the efficiency in detecting true positives as given by values ranging from 97.22% to 100% under Poisson noise and from 97.22% to 100% under thermal noise. This indicates that ResNet18 can be reliably employed for signal detection from the desired source without neglecting them due to interference caused by noise.

Similarly, specificity scores are consistently high, implying the ability to accurately determine true negative signals using this model. For instance, using Poisson or thermal noises, these results range between 98.59 and 100% across all subclasses under [7]. Thus, the absence of signals from the intended source may also be separated from those alarms originating through noisy environments by ResNet18, as it does not raise any false positive alarms in other instances [14].

TABLE II. EVALUATION MEASURES FOR MULTI-CLASS CLASSIFICATION

CNN Type	Noise	Sub-Class	Accuracy	Sensitivity	Specificity	Precision	F1 score
VGG19 Net	Poisson	UMTS Waveform	92.86	95.59	96.48	92.86	94.20
		LTE Waveform	97.14	94.44	98.55	97.14	95.77
		5G NR Waveform	95.71	95.71	97.86	95.71	95.71
		Average	95.24	95.25	97.63	95.24	95.23
	Thermal	UMTS Waveform	95.71	98.53	97.89	95.71	97.10
		LTE Waveform	97.14	97.14	98.57	97.14	97.14
		5G NR Waveform	98.57	95.83	99.28	98.57	97.18
		Average	97.14	97.17	98.58	97.14	97.14
ResNet18	Poisson	UMTS Waveform	98.57	98.57	99.29	98.57	98.57
		LTE Waveform	97.14	100	98.59	97.14	98.55
		5G NR Waveform	100	97.22	100	100	98.59
		Average	98.57	98.60	99.29	98.57	98.57
	Thermal	UMTS Waveform	100	100	100	100	100
		LTE Waveform	100	98.59	100	100	99.29
		5G NR Waveform	98.57	100	99.29	98.57	99.28
		Average	99.52	99.53	99.76	99.52	99.52

Both models have strong identification capabilities during signal tasks. ResNet18 performs slightly better than most scenarios, especially in Thermal noise conditions. Nevertheless, VGG19 Net performs well in sensitivity, specificity, precision, and F1 scores. Precision is the fraction of correct positive predictions, whereas the F1 score is a harmonic average between precision and recall (sensitivity). These measures help assess the balance between false positives and false negatives, which may influence the efficiency and reliability of signal identification.

The F1 scores for both models show that they have balanced performances both ways in terms of precision and recall – these are fundamental aspects for effective signal identification among various noises. As such, the choice between them will depend on specific application requirements and priorities. However, both VGG19 Net and ResNet18 typify how CNN architectures are relevant in accurately determining signals against changes in noise levels, which have improved signal processing developments. Figures 6, 7, and 8 show the evaluation performance values of the models.

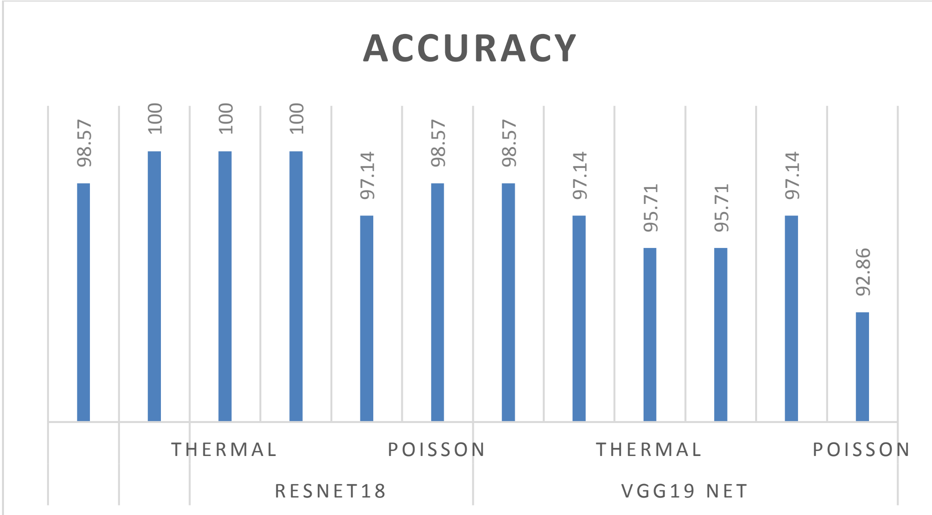

Figure 6. Average Accuracy

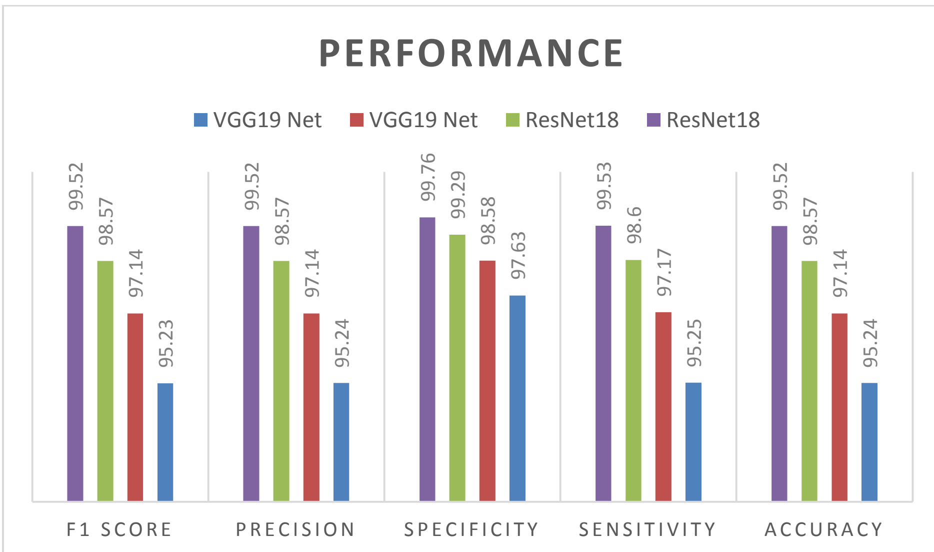

Figure 7. Performance analyses

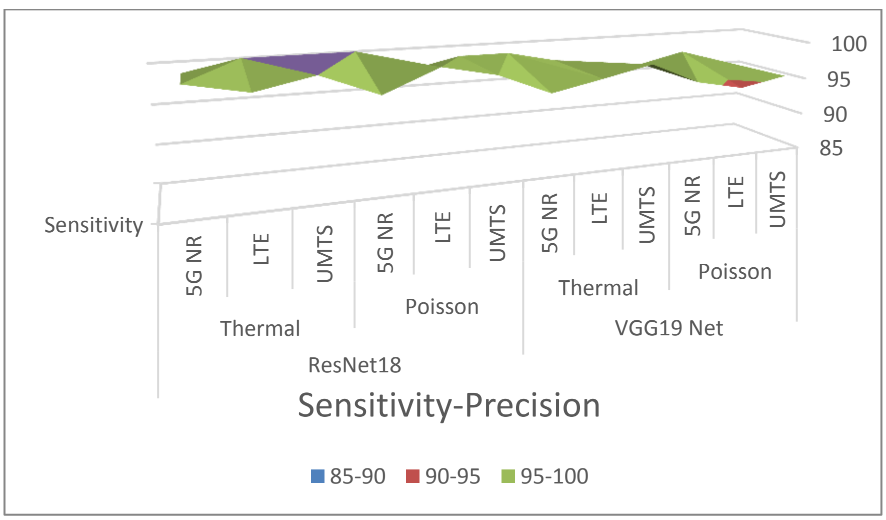

Figure 8. Sensitivity-Precision

Confusion matrix values depict the noise conditions for each class, as shown in Table III. In Poisson noise, VGG19 Net provides TP values of 65 for UMTS, 68 for LTE, and 67 for 5G NR, indicating that it can perform a pretty good classification on different signals. Meanwhile, ResNet18 has slightly higher TP values than VGG19 Net under Poisson noise conditions, such as achieving 69 UMTS, 68 LTE, and 70 for 5G NR. It should be noted that within this range, ResNet18 performs better, specifically in distinguishing the two classes of UMTS and 5G NR. Notwithstanding the thermal noise, both architectures maintain almost similar performances, with VGG19 Net having TP values of (67,68,69) respectively, while ResNet18 sustains TP values of (69,68,70). These results show that ResNet18 generally does somewhat better with a slight advantage over VGG19 Net, especially under Poisson noise. Furthermore, significant differences in correctly identifying signals like LTE compared to UMTS or even 5G NR indicate the importance of considering signal complexity and noise sensitivity during robust communication system design. Such knowledge can help when choosing CNNs appropriately, along with approaches aimed at mitigating noises for applications about signal processing, hence making communication dependable systems.

Table III. CONFUSION MATRIX

	CNN Type	Noise	Sub-Class	UMTS Waveform	LTE Waveform	5G NR Waveform
1	VGG19 Net	Poisson	UMTS Waveform	65	1	2
			LTE Waveform	3	68	1
			5G NR Waveform	2	1	67
		Thermal	UMTS Waveform	67	1	0
			LTE Waveform	1	68	1
			5G NR Waveform	2	1	69
2	ResNet18	Poisson	UMTS Waveform	69	1	0
			LTE Waveform	0	68	0
			5G NR Waveform	1	1	70
		Thermal	UMTS Waveform	70	0	0
			LTE Waveform	0	70	1
			5G NR Waveform	0	0	69

V. CONCLUSION

In this paper, deep learning is used to identify signals. Cellular system environments are focused and consider the possibility of signals such as UMTS(3G), LTE (4G), and 5 G. Signal classification tasks are carried out using two different convolutional neural network architectures, specifically VGG19 and ResNet18. The performance of these CNN architectures in classifying signals accurately amidst noise and fading effects is systematically assessed through thorough experimentation. About different wireless communication standards, VGG19 and ResNet18 neural network models have shown robust abilities for signal identification purposes in this study. However, despite SNR level fluctuations and Rayleigh fading effects, the models consistently achieve high classification accuracy. ResNet18 performs better concerning Poisson noise cases, thus demonstrating its potential application in practical signal identification cases. To ensure the reliability and generalizability of results, a 5-fold cross-validation approach illustrates how resistant models are to noise and fading phenomena. ResNet18 demonstrated a commendable average accuracy of 99.52%, while VGG19 Net demonstrated 97.14%.

This study lays the groundwork for further research and improvement of wireless communication systems, highlighting the significance of deep learning in making signal identification more dependable and effective. By capitalizing on sophisticated CNN architectures, doors are open toward futuristic networks that can flawlessly assimilate state-of-the-art technologies, propelling advances in this area. These findings also promote this understanding and application of deep learning techniques by emphasizing the need for robust CNN architectures that can be used to identify signals reliably, even in the most complicated communication environments.

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