Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

Deep Learning Strategies for 5G and LTE Spectrum Sensing Communication

Suham A. Albderi*

Al-Furat Al-Awsat Technical University, 31003, Najaf, Iraq.

*Corresponding Email: *Kin.shm@atu.edu.iq*

Received: 14 October 2023 **Accepted:** 30 December 2023 **Published:** 17 February 2024

Abstract: The idea of 5G innovations is a prevalent instrument for the pace of transmission and gathering of data and the accessibility of permitting all over the place. Notwithstanding that the fifth era convergences will embrace a keen procedure for the data transmission process. Sending and getting signals work in high coordination in 5G networks, since this innovation arranges flexible, geostationary earthbound correspondence with other medium and little circuit correspondences with short steering in straight correspondences, and the correspondence incorporates signal processing as well as way finding. In this study the responsiveness improvement of the correspondence range will be tested by applying blended deep learning methods, in which the data cross-over will be diminished with the upgraded smart control. Utilizing blended deep learning methods, this study exhibits the huge difficulties presented by 5G transmissions in keenly detecting the LTE signal range and different data in 5G remote sensor networks. Way obstructions are recognized as the essential hindrance. The states of the correspondence framework ought to be considered while plotting the network and sensors for the fifth era.

Keywords: 5G Innovations, Remote Sensor Networks (WSNs), Deep Learning Strategies, Execution Improvement, LTE Detecting.

1. INTRODUCTION

Future wireless communication systems are at risk technological issues due to the rapid increase in mobile data despite the lack of spectrum resources. During the in past years, cognitive radio (CR) was widely used investigation as a solution to alleviate spectrum problem underutilization caused by fixed allocation of radio frequencies spectrum, by sharing spectrum among licensees Primary Users (PU) and the unauthorized Secondary Users (SU). The volume of data being transmitted today is unprecedented for wireless communication systems. To meet demand, wireless communication networks must make the most efficient and efficient utilize of the limited spectrum available. Additionally, the implementation of small cells, the utilization of mmWave frequencies, efficient spectrum utilization algorithms, extensive multiple-input

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

multiple-output (MIMO) structures, with cognitive radio networks all work toward the similar objective. By dynamically distributing the spectrum among users, cognitive radios aim to fulfill this objective; As a result, cognitive radio network techniques like spectrum sensing with waveform recognition emerged as major ones. Since 5G and beyond will require joint communications, sensing, and localization, robust allocation of spectrum will be even further important for heterogeneous networks. Dynamic spectrum sharing, such as, is a novel approach that enables simultaneous process of 5G and Long-Term Evolution (LTE) in the similar frequency in 5G NR release [1-3]. The classical sensing paradigm cannot meet the demands of the rapidly changing operating surrounding of instant with eventual remote transmitting networks because such a cumbersome procedure can hinder the activity decision-making demands of 5G against networks. In such context, deep learning (DL) has been suggested as a way to solve the problem of conventional strategies parameter adaptation.
This is because DL methods are known to use a convolutional process to extract the intrinsic features of inputs. At the conclusion of the identification process, a statistical decision mechanism is not required because DL-based approaches are used instead. In this regard, a recent study demonstrates that DL approaches succeeds conventional techniques for spectrum waveform reception. A smart radio analysis for spectrum sensing with waveform recognition is needed to meet the demands of 5G and without remote networks. Such results might be accomplished using the assistance of machine learning (ML) techniques, which make use of features like the signals cyclic stability [4-6].

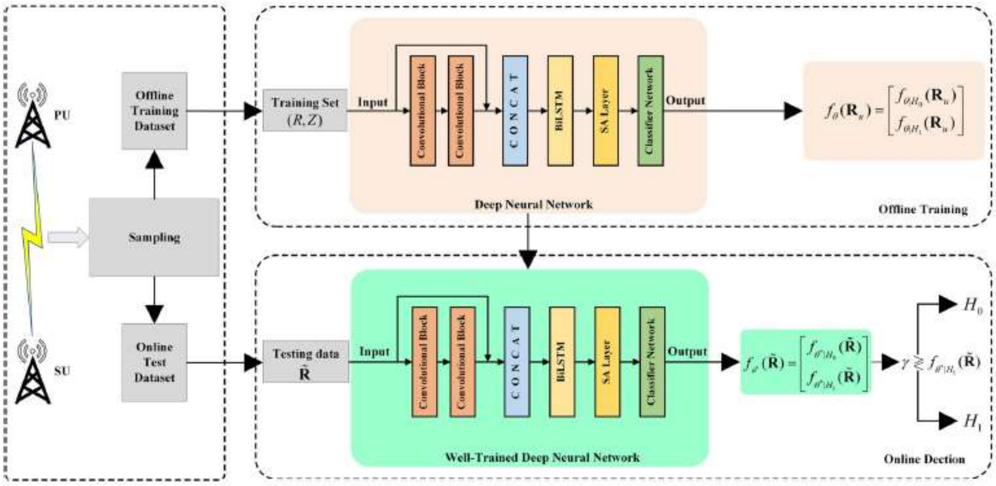


Figure 1: Typical 5G LTE spectral sensing deep learning technique block diagram [3-6].

2. RELATED WORK

In this segment, we will audit the most famous examinations and significant ongoing papers that anyone could hope to find with research articles connected with the subjects of 5G and LTE signal spectrum sensing using deep learning strategies. Significant examinations will sum up the creators' endeavors on this point in a high level scientific arrangement. Knowledge procedures for range detecting and sign ID are utilized in a writing survey of further developing 5G range

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

detecting themes. It thinks about the nature and intricacy of the framework, and at first expands on that by utilizing high-request convolutional brain organizations (CNN) preparing with single transporter signal insights for tweak order [9]. In 2018, M. Kulin, et. al., [10], utilized fast Fourier transform (FFT), amplitude phase illustration (AP), as well in-phase/quadrature (I/Q) appearances for exercising, a CNN classifier is utilized to identify interference with modulation in industrial scientific medical (ISM) bands. In 2019, R. Miller, et al., [11], concentrated on the industrial scientific medical (ISM) band protocol classification utilizing fully attached neural networks (FCNNs). In 2019, W. Meert, et al., [12], Long short term memory (LSTM) is applied in this study for modulation designation against recognition of digital video broadcast (DVB), LTE, Global System for Mobile Communications (GSM), and wide-band FM (WFM) waves by applying AP with FFT capacity for testing as alternative exercise of the implementation of DL to waveform distribution. In 2006, N. Han, et. al., [13], presented that cyclostationary features detection (CFD) is a well-established technique for spectrum sensing in the cognitive radio domain. It is also used to recognize qualitative modulations like M-PSK, M-FSK, and M-QAM. In 2013, A. Hazza, et. al., [14] showed that CFD relies on likelihood-dependent approaches as well numerical resolution techniques to select the underlying appearances. For the sake that CFD to function in the productive altering transmission channel, an additional strategy is needed to adaptively control decision components like thresholds and the samples sum. In 2019, S. Ramjee, et. al., [15], demonstrated a comparative analysis for the purpose of training DL networks, to illustrated that that SCF outperforms I/Q, AP, and FFT features. In 2017, G. Huang, et. al., [16], performed comparisons against existing DL techniques like traditional long little term storage fully connected deep neural network (CLDNN), LSTM DenseNet, with ResNetin in conditions of accuracy, storage expenditure, as well evaluation complication. In 2021, Ali Rıza Ekti, et. al., [17], suggested a technique that beats support vector machines (SVMs) prepared against SCF, that is our past review. Also, the exhibition of the suggested strategy in this study is contrasted and the old style range detecting method of CFD, that demands the cyclic bands as deduced data.

3. METHODOLOGY

3.1 Spectral Sensing Theory

Recently, technologies based on machine learning raised to sense the spectrum, she is unable to implicit and competent learning wireless surround environment. Moreover, these technologies appear to be so more adapted to the dynamic changes of the environment, compared to traditional methods [7]. To date, most of the works on spectrum sensing using machine learning when manually extracting the feature. For example, the authors in [8] and [9] suggest a technical neural network (ANN) and convolutional neural network (CNN) for spectrum sensing respectively, utilizing energy- and cyclostationarity-dependent features along the received waveform. Ann-based spectrum sensor utilizing classical energy detection and likelihood ratio statistics suggested in [10]. One significant disadvatage to such guide the benefit extraction is that the entire network should be he was retrained by collecting a whole new set of data whenever he was the input signal feature changes. Its auto extraction feature the literature on spectrum sensing was also investigated by deep learning [11,12]. Thus, the deep neural network (DNN) scheme must be it is retrained every time the site with environment is subjected the

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

changes. This will require combining advance datasets on every new remote sites and environments. As a training it demands a large amount of periods, data and computations resources it is impractical to combie advance datasets as well to retrain the structure every time such changes exist [10-12]. Therefore, in this thesis, we consider spectrum sensing an issue with the entanglement scenario, where a single SU performs sensing along deep learning with automatic feature extraction. The objective of our suggested approach is mitigation the issue of collecting advanced data sets and retraining DNN whenever the features of the entered waveform undergo variations [12-14]. The complicated modulating signal frequency cpmparable of the detected waveform, r(t), mudt first be determined, assuming that it is downward transformed to modulating signal prior to extra operating. When there is thermal noise and a fading environment, the received signal might be produced as:

$$r(t) = \rho(t) * x(t) + \omega(t) \tag{1}$$

Where the complicated additive white Gaussian noise (AWGN) frequency ω is represented by ω(t) and CN(0, σ_N^2) in the shape of ω(t) = $\omega_I(t) + j\omega_Q(t)$ as both $\omega_I(t)$, $j\omega_Q(t)$ become $\mathcal{N}$= (0, $\sigma_{N/2}^2$), and j =$\sqrt{-1}$, *x*(*t*) is the complicated modulating signal comparable to the sended waves, because of the severely shortened perception time of a waveform, ρ(t) determinds for the remote channel time-invariant impulse response. The deep learning techniques of the waveform recognition operation might be modeled as a binary theorem examination based on the mobile propagation channel's idle or busy state in the RF spectrum.

$$r(t) = \begin{cases} \rho(t)x(t) + \omega(t), & H_1 \\ \omega(t), & H_0 \end{cases} \tag{2}$$

The H_0 and H_1 hypotheses represent the unknown signal and only the presence of noise, respectively. Consequently, the existance of the unknown waveform could be used to represent the problem statement, *x*(*t*), and its classification.

3.2 The Cyclostationary Signal

Using cyclostationary signal processing, *r*(*t*), covered revolutions in a detected wave might be extracted. The data required for identification is provided by these periodicities, such as spreading codes, symbol instants, and guard periods, which have distinct attributes for various waves. Consequently, in the absence of a priori information, the numerical attitudes of *r*(*t*) in the existance of ω(t) with multipath fading might be utilized to identify the unknown signals *x*(*t*). A signal's second-order cyclostationarity, a nonlinear transformation, might be represented as:

$$s(t) = \mathbb{E}\left\{r\left(t + \frac{\tau}{2}\right) r * (t - \frac{\tau}{2})\right\} \tag{3}$$

whereas r(t)'s autocorrelation is represented by $s_\tau(t)$. A Fourier series expansion of $s_\tau(t)$ is provided as, assuming that the autocorrelation function for second-order cyclic stationary waveforms is periodic with T_0.

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

$$\mathbb{R}_r^\alpha(\tau) = \frac{1}{T_o}\int_{-T_o/2}^{T_o/2} s_r(\tau)\, e^{-j2\pi\alpha t} \quad (4)$$

Such that, $\mathbb{R}_r^\alpha$, denoted the "cyclic autocorrelation function" (CAF), also α, amounts represent the cyclic frequencies. Next, the (CAF) Fourier transform for a settled, α, is obtained using Wiener equation [12] such as:

$$\mathbb{S}_r(f) = \int_{-T}^{T} \mathbb{R}_r^\alpha(\tau)\, e^{-j2\pi f\tau} d\tau \quad (5)$$

In which, $S_r(f)$, corresponds to the "power spectral density" (PSD) at 0. The PSD calculation has a relatively high computational complexity. However, the FFT accumulation approach dependent on instant sharpening with FFT might minimize such complexity [10-14]. According to the "Fourier Accumulation Method" (FAM), the PSD might be written such that:

$$\mathbb{S}_{r_T}(f) = \sum_k R_T\,(KL, f) R_T{}^*(KL, f) g_c(n-k) e^{i2\pi kq/P} \quad (6)$$

in which $R_T\,(n, f)$ represents the complicated demodulates, which are the N'-point Hamming window FFT of $r(n)$ that might be estimated by [12-14]:

$$R_T(n, f) = \sum_{k=-N'/2}^{k=N'/2} a(k) r(n-k)\, e^{i2\pi(n-k)T_s} \quad (7)$$

Whereas data tapering windows are $a(n)$ and $g_c(n)$. The channelization distance, sampling interval, and sample extent of hopping blocks are represented by the symbols; N', T_s, and L, respectively. The second FFT's length, denoted by P, is determined by the ratio amidst the sum of overall elements against L. The FAM has six implementation steps. Channelization, windowing, N'-point FFT, complex multiplication, P-point FFT, and bi-frequency mapping are the respective steps. As $g_c(n)$ and $a(n)$, respectively, the unit rectangle and Hamming windows are utilized in the research. Figure 2 displays the estimated PSDs with noise for GSM, UMTS, with LTE from the FAM strategy in the bi-frequency plane. Consequently, the classifier model's entered array, X_k^{SCF}, has achieved as [12-16]:

$$X_k^{SCF} = \left|\mathbb{S}_{r_T}(nL, f\right| \quad (8)$$

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

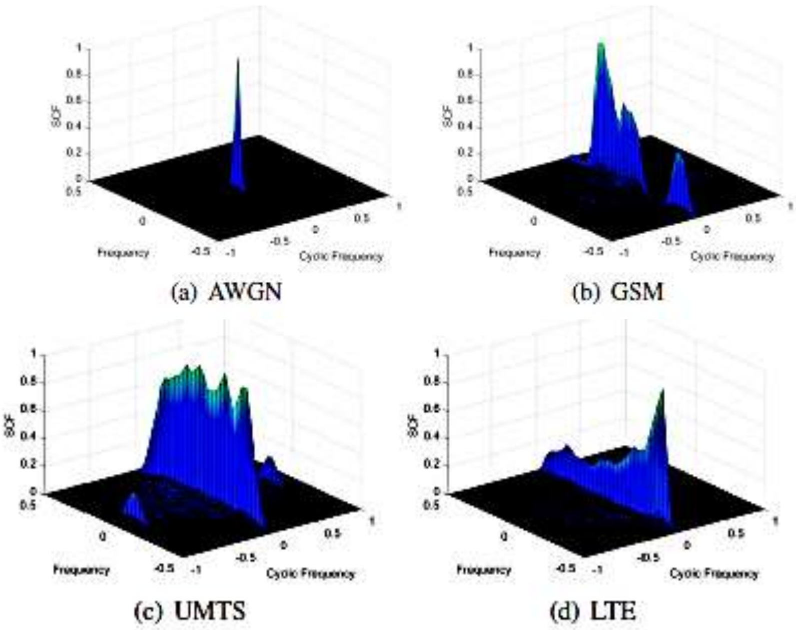


Figure 2: Estimations of cellular waves in the bi-frequency surface made by PSD using FAM. The various cyclic characteristics of the signals might be simply observed. Since the noise's PSD just yields a amplitude at the middle of the bi-frequency surface, where the cyclic frequency is zero, the noise exhibits no cyclic characteristics [10-14].

2.3 The Convolutional Neural Network (CNN) Strategy

The idea of spectral sensing using the convolutional neural networks (CNN) algorithm has been delineated obviously in the past area. The entered preparing data to the CNN algorithm will be pictures of the spectral parts of the distinguished or got signal. These pictures will be examined through the elements channels given by the CNN algorithm to categorize the states of each detected signal range. After this part, the sifted pictures will be placed to the convolutional layer which will contrast among them with decide the varieties with each spectral signal picture. Then, the prepared sifted and convolved data pictures will be gone through the most extreme pool layer that will recompute the thickness or amplitudes of each prepared picture data to resize them. Figure 3 presents a schematic chart of the CNN algorithm structure used in the spectral sensing strategy [10-16].

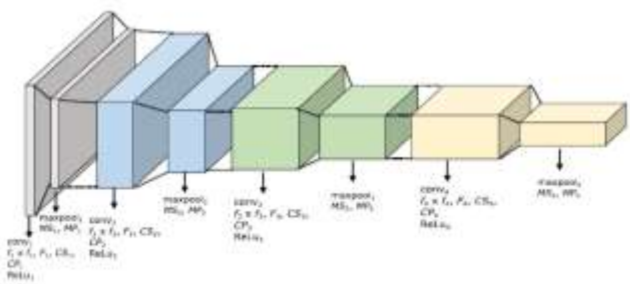


Figure 3: The CNN algorithm architecture utilized for spectral sensing and feature extraction [10-16].

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

By considering the structure shown in Figure 3, we might observe the filtered and parsed trained data images will be access along the max pooling layer which will recalculate the density or amplitude of each trained image data in order to resize it. These are the main operations provided by the CNN algorithm which might be repeated in multiple partitions for more accuracy and detection quality. Moreover, a sensor decision module or Relu function will be added to the CNN algorithm structure to complete the detection evaluation. This Relu function will produce a mathematical transformation to the detected data so that it is suitable for extracting the final results. Furthermore, Figure 4 illustrates a block diagram of the spectral sensing methodology with the traditional approach and against the CNN algorithm one.

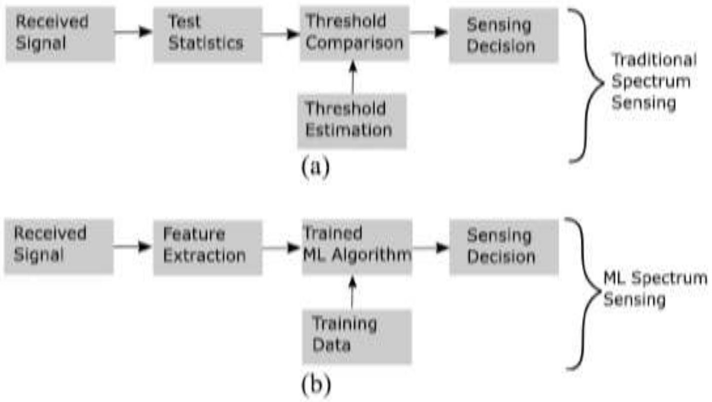


Figure 4: Spectral sensing methodology (a) Applying the conventional method and (b) Employing ML-based methods [10-18].

By regarding the details presented in Figure 4, we could notice the traditional spectrum sensing will depend on the threshold estimation and comparison which is basically depends upon the test statistics as illustrated in Figure 4.(a). Whereas, in the second block diagram, the spectral sensing will depend on the CNN algorithm operation and the learning of the training data with feature extruction technique. Hence, a general block diagram of the CNN algorithm structure operations necessary for spectral sensing technique is shown in Figure 5 [16-20[.

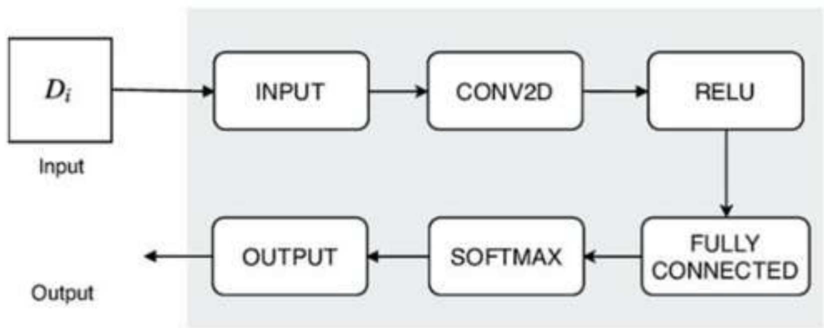


Figure 5: Block diagram of the CNN algorithm general structure[16-20].

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

Thus, by considering the blocks introduced in Figure 5, we might observe the overall spectrum sensing CNN algorithm structure might be summarized with the illustrated 6 interal sections or layers; input layer, two dimentional convolutional layer, Relu function, fully connected layer, softmax or max pooling layer, and the output layer. Hence, the wireless communication RF spectrum sensing technique suggested in this work will completely realy upon this CNN algorithm strategy. Deep neural networks of the CNN kind are mostly utilized for classification and recognition of picture. CNN processes entries like a human video model. To put it another way, rather than fitting data, it extracts features from an input [18-25].
In this Part, the strategy of the recommended model of 5G and LTE Signal Range Sensing utilizing Deep Learning Techniques has been desicribed and outlined using MatLab2020b Simulink model. This product contains a thick library giving the creator every vital device, blocks, supporting frameworks, and measurments types of gear which will help to reproduce any modern framework in PC Figure 6 shows the simulated interface of the deep learning (CNN) spectral sensing technology design used in the project.

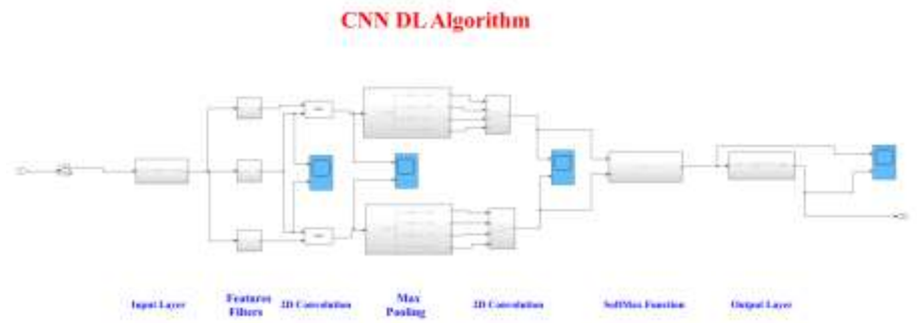


Figure 6: The simulink design of the CNN DL algorithm spectral sensing model.

By concerning Figure 6, we might observe the detailed costruction of the CNN DL algorithm utilized for spectral sensing technique in our suggested model. The iternal sections of the CNN DL algorithm will be illustrated and comprehented in the below discussion.
The flow diagram of the CNN classification process will be demonstrated in Figure 7.

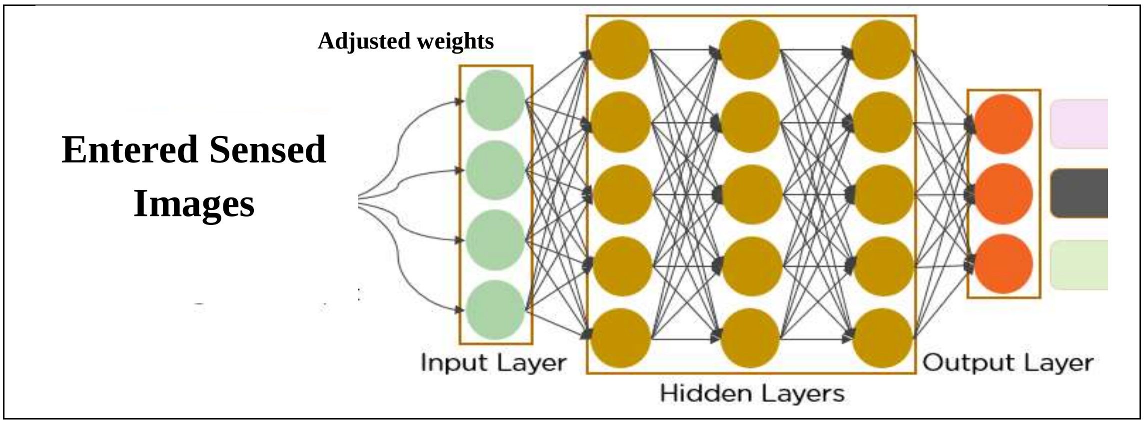


Figure 7: The structure diagram of the CNN classification process.

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

Also, the CNN algorithm structure from entering data to the output results have shown in Figure 8, below.

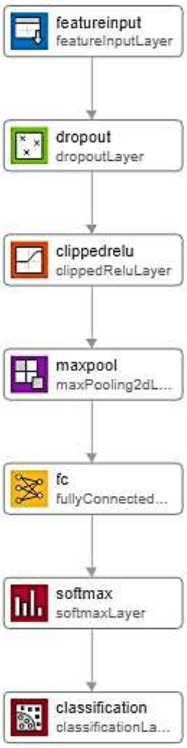


Figure 8: Structure of implemented CNN algorithm.

The entered spectral data images sets have been examined using the CNN Classification Learner to train the model using several classifications stages. The specifications of the suggested 5G and 6G WSN communication frameworks for intelligent control of data interference QoS is presented in Table 1.

Table 1: Specifications of the suggested 5G wireless communication spectral sensing model.

Techmology Type	**Data Frequency f_m (Hz)**	**Bit Rate R_b (bps)**	**Carrier Frequency f_C (Hz)**	**Sampling Time T_S (sec)**	**SNR (dB)**
5G	$1*10^6$	$1*10^6$	$100*10^6$	$1*10^{-7}$	5

4. SIMULATION RESULTS & DISCUSSION

The suggested model of RF wireless communication spectral sensing using deep learning CNN algorithm has been successfully designed, simulated, and implemented and the achieved results have been recorded according to the signal transfer through each unit in the RF wireless

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

communication model. At the beginning, the obtained analog message signal from the radom signal geerato is shown in Figure 9.

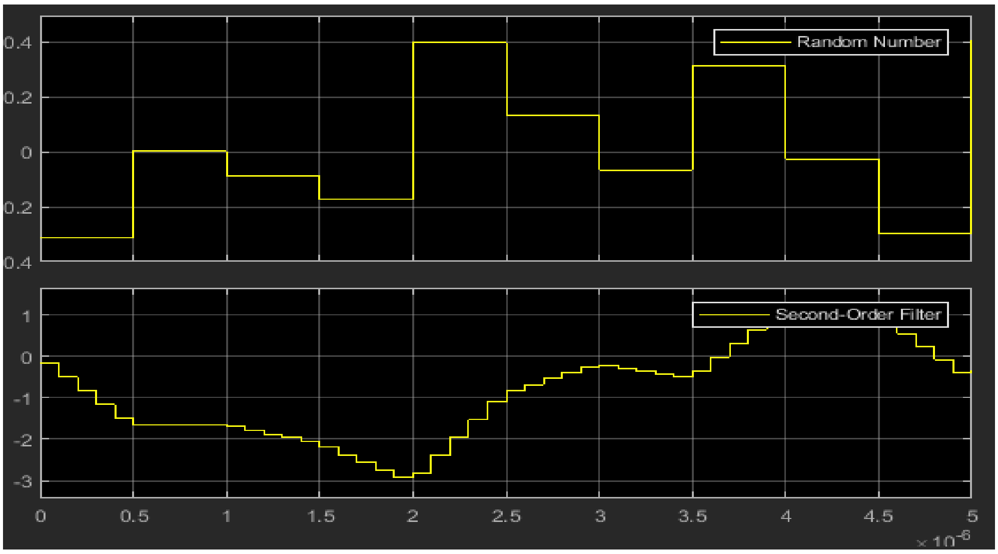


Figure 9: The achieved analog message signal from the signal generator.

By regarding the message signal displayed in Figure 9, we might observe that the resulting waveform will be an analog signal from the random generator with continous shape and frequency band of 1 MHz that satisfy the audio/video frequency range. Next, this message signal will be converted to digital sequences using analog to digital converter (ADC) system in order to prespare the message signal to be digitally modulated with the digital transmitter unit. Figure 10, presents the message signal in both analog and digital form before and after the ADC system.

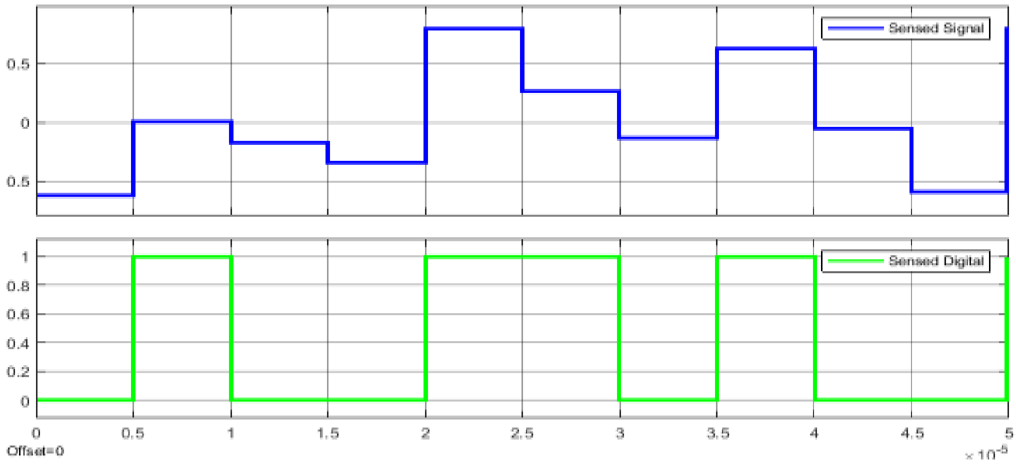


Figure 10: The message signal in both analog and digital form before and after the ADC system.

By noting the results introduce in Figure 10, we might conclude that the resulting waveform with green color will be an digital sequence from the analog message signal with blue color with the same frequency band of 1 MHz for the same audio/video frequency range. Now, applying

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

Fourier transform to the resulting sequence shown in Figure 10, the spectrum response of the transmitted message waveform will be obtained as demonstrated in Figure 11.

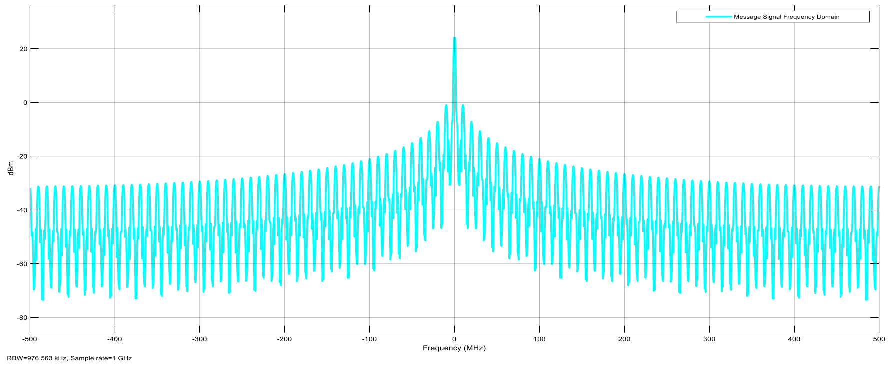


Figure 11: The obtained spectrum response of the transmitted message signal.

By observing the signal presented in Figure 11, we might notice that, the achieved spectrum of the message waveform will have bandwidth of 1 MHz that produce maximum frequency contents power of 20 dB. Whereas, the other spectral contents of the frequency response will have reduced power with -20 dB. Moreover, the next stage will be the transmitter unit such that the OFDM modulator will operate to carry the message signal upon the carrier reference frequency. The OFDM transmitted signal is produced with carrier frequency of fc=100 MHz. spectrum of the message waveform will have bandwidth of 1 MHz that produce maximum frequency contents power of 20 dB. Whereas, the other spectral contents of the frequency response will have reduced power with -20 dB. Also, the spectrum of the OFDM modulated signal is obtained by performing Fourier transform as displayed in Figure 12.

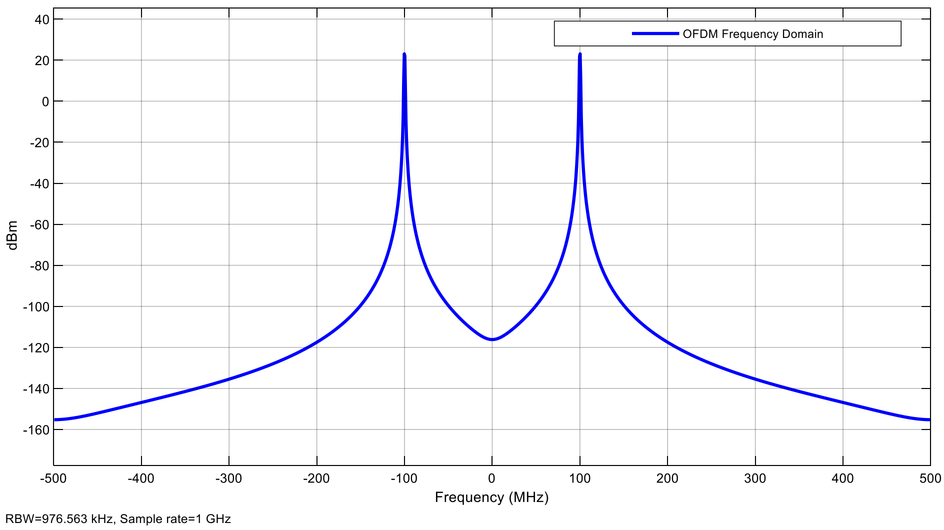


Figure 12: The spectrum of the OFDM modulated signal is obtained by performing Fourier transform with f_c=100 MHz.

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

Furthermore, the OFDM modulated signal will pass through the AWGN communication channel which will add random noise with SNR of 100 dB to the transmitted waveform such that it will be corrupted with this random noise samples. The resulting corrupted OFDM signal after passing through the AWGN channel is shown in Figure 13.

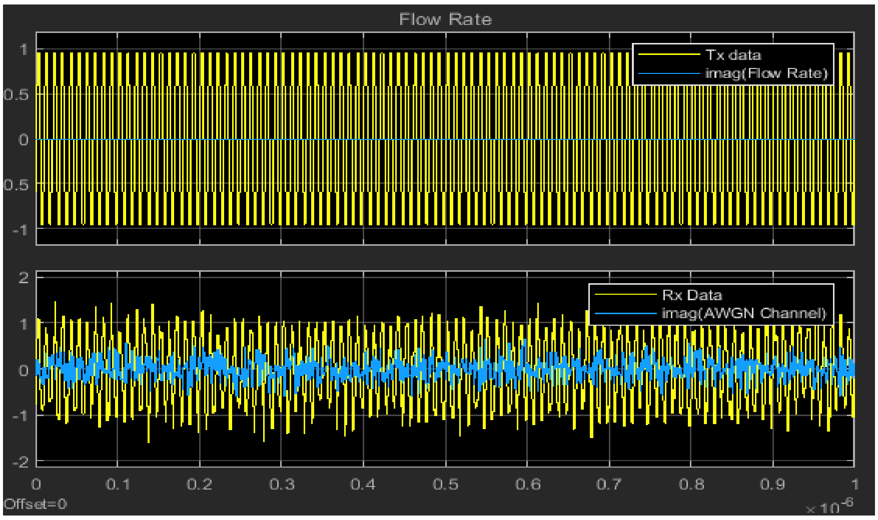
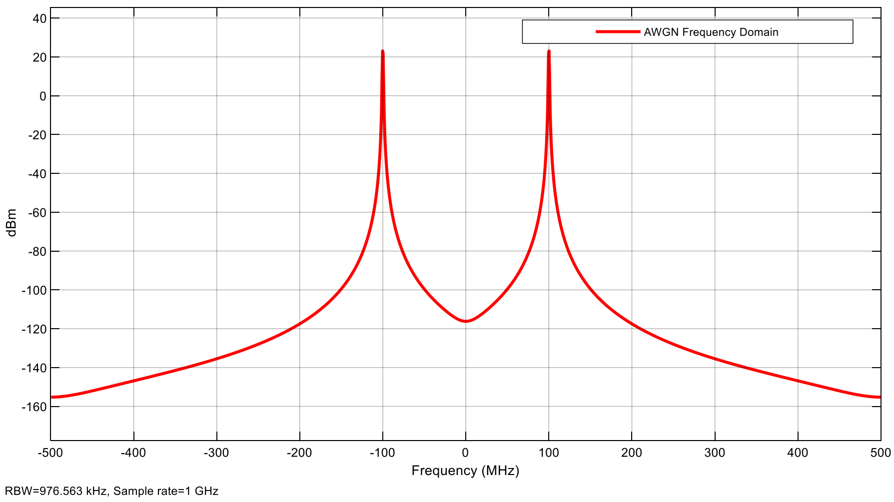


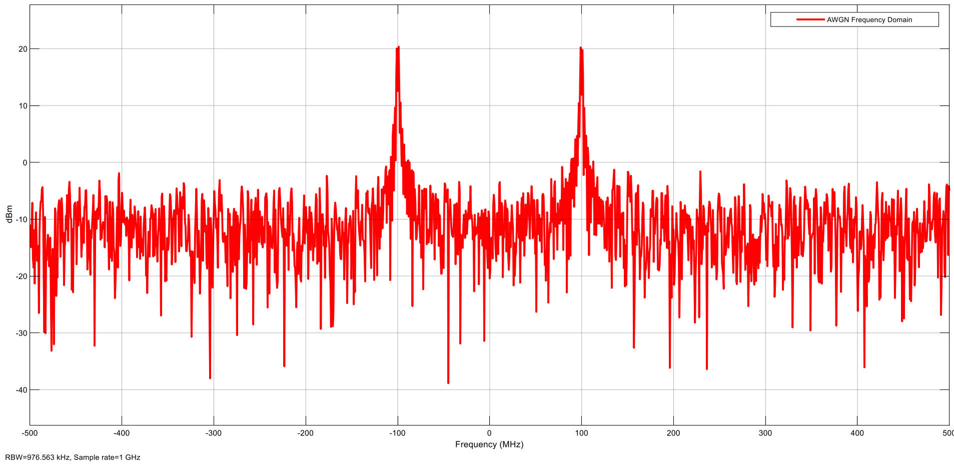
Figure 13: The obtained corrupted OFDM signal after passing through the AWGN channel.

Thus, and regarding the waveforms presented in Figure 13, we could observe the OFDM modulated signal appeared in the upper half of the Figure will pass through the AWGN communication channel and will be distorted with the random noise samples with SNR of 100 dB as appeared in the lower half of the Figure. We might notice the effect of the noise signal on the transmitted OFDM wave, which appears as a random signal in blue, which affects the purity of the embedded waveform and hence the quality of the received data signal. Next, the spectrum of the distorted OFDM waveform passing through AWGN channel has been achieved utilizing spectral analysis as displayed in Figure 14.



(a)

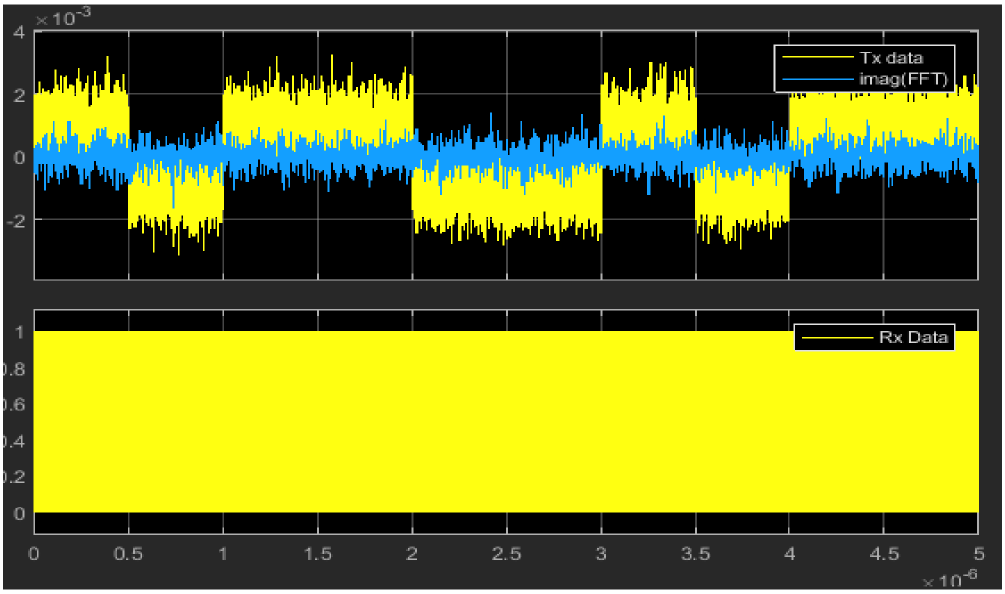
Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29



(b)

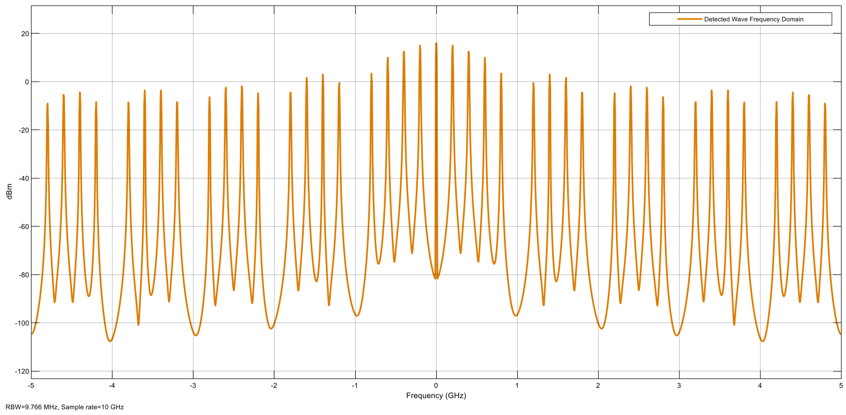
Figure 14: The achieved spectrum of the distorted OFDM signal passing through AWGN channel using spectral analysis, (a) Before, and (b) After AWGN channel.

Thus, and concerning the spectra introduced in Figure 14, we might notice that the OFDM modulated wave spectrum remain with no changes before the AWGN channel appeared in the upper half of the Figure. On the lower half of the Figure, the spectrum of the OFDM transmitted signal is observed with random distortion spectral samples appeared due to the addition of the random noise signal by the AWGN communication channel. In this design, the distorted random noise samples have SNR of 100 dB which will produce little noisy samples those will corrupt the overall transmitted OFDM waveform. Moreover, the resulting signals after passing though the QPSK digital demodulator are demonstrated in Figure 15 in time and frequency domains.



(a)

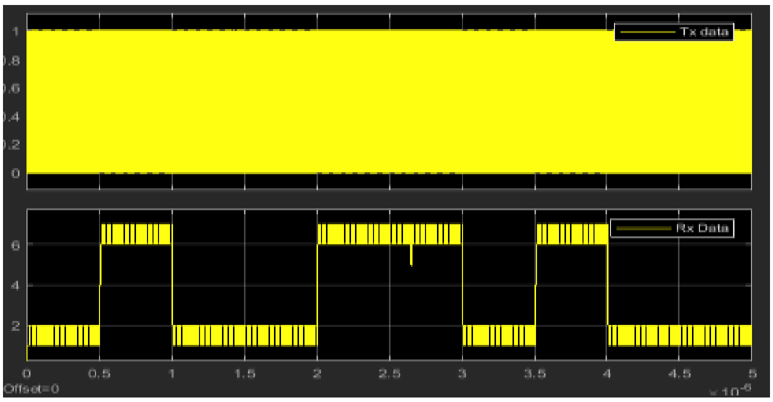
Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29



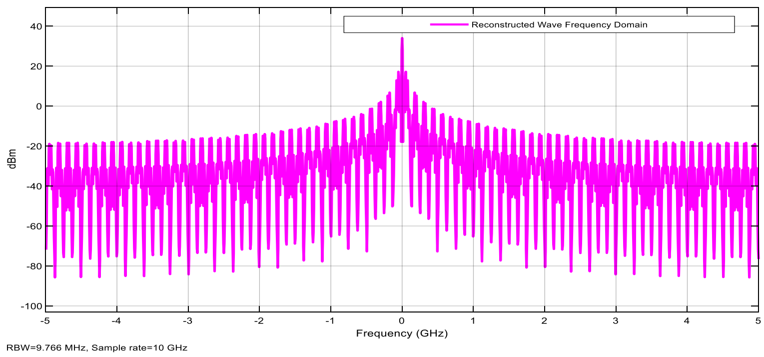
(b)

Figure 15: The resulting signals after passing though the QPSK digital demodulator, (a) The time domain, (b) Frequency domain.

At last, applying sample and hold system for further filtering the spectral copies of the repeated frequencies and extruct the original transmitted message signal. We will obtain the original digital transmitted message waveform as displayed in Figure 16 in bothe time with frequency axis.



(a)

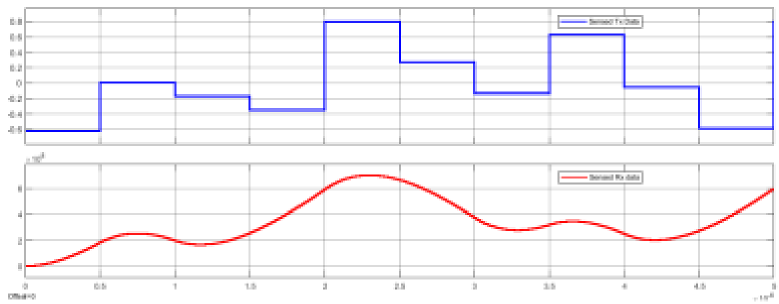


(b)

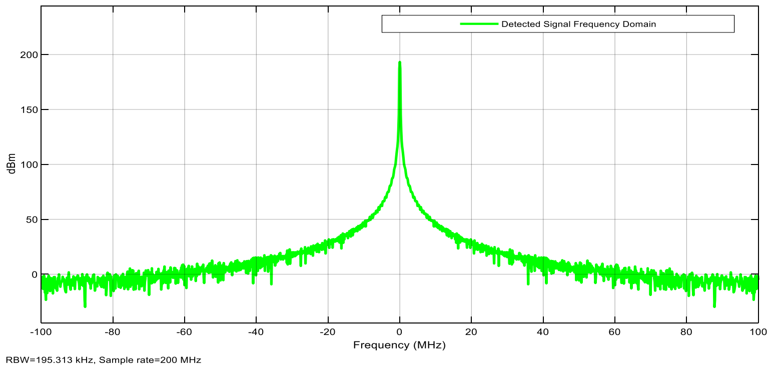
Figure 16: The resulting signals after passing though the sample & hold detector, (a) Time domain, (b) Frequency domain.

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

Now, regarding the spectral sensing technique, we have employ two approaches, the FFT technique and the CNN DL algorithm strategy to analyze the received OFDM signal. Thus, the reconstructed original message signal in digital and analog form will be achieved due to FFT spectral sesing technique as displayed in Figure 17.



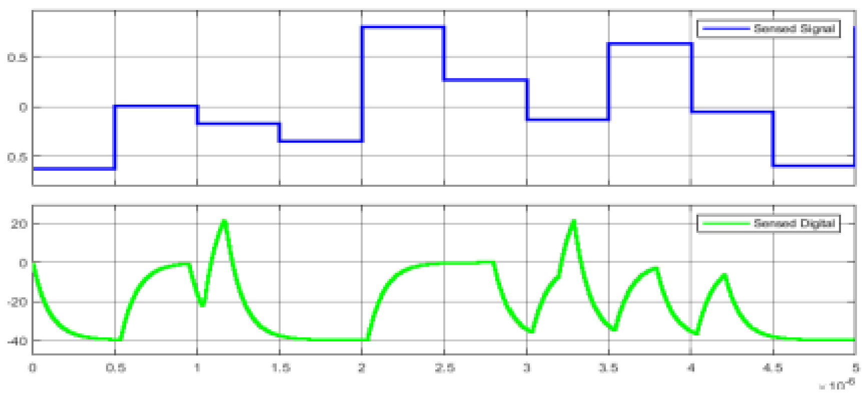
(a)



(b)

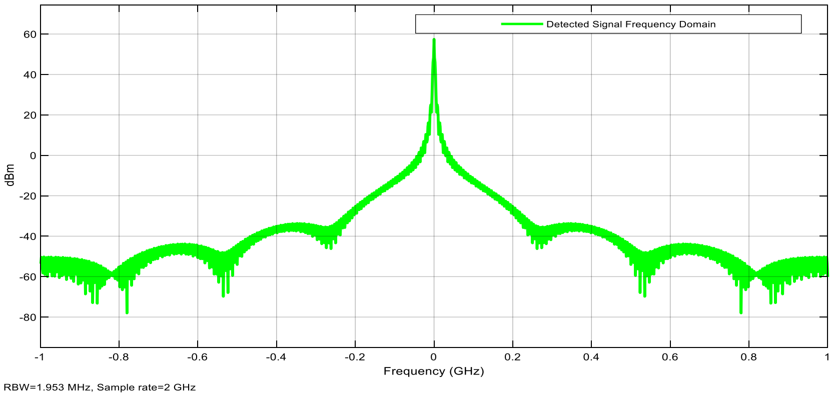
Figure 17: The reconstructed original message signal in digital and analog form will be achieved due to FFT spectral sesing technique, (a) Final detected time domain data, and (b) Final detected spectrum.

Now, the final spectral sensing detected signal using deep learning CNN algorithm, showing the initial detected data, the final detected data, the initial detected spectrum, and the final detected spectrum are presented in Figure 18.



(a)

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29



(b)

Figure 18: Final spectral sensing detected signal using deep learning CNN algorithm, (a) Final detected data, and (d) Final detected spectrum.

At last, the comparison amidst the digital detected and the transmitted message waves are achieved as illustrated in Figure 19.

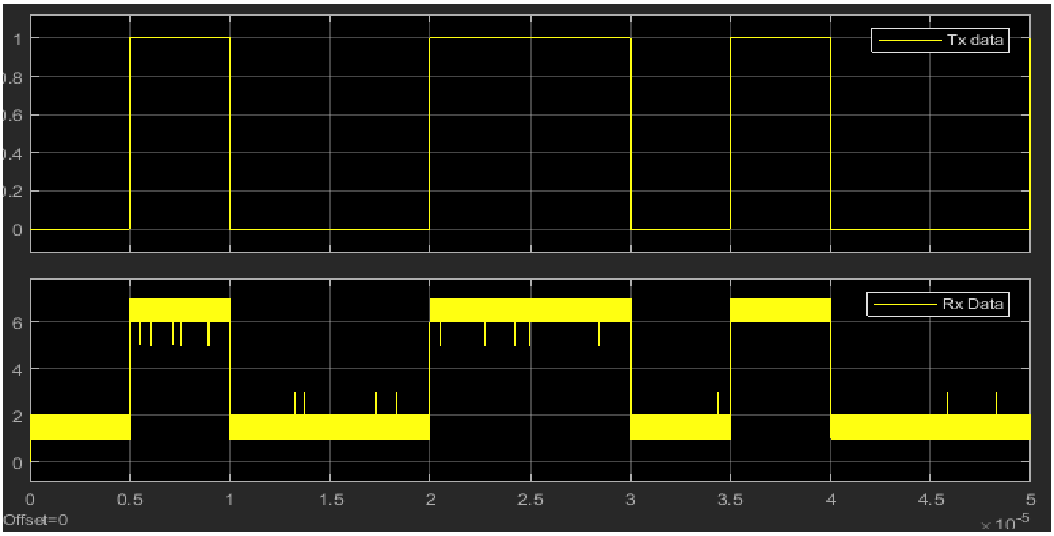


Figure 19: Final achieved comparison amidst the digital detected and the transmitted message waves.

At last the achieved results of the spectral sensing FFT and CNN algorithm performance will be tabulated according to the table illustrated below:

Table 2: Results of the CNN classification algorithm.

Classification Kind	**CNN**	**FFT**
Bit Error Rate	10^{-2}	10^{-2}
Accuracy	88 %	86%
Error	12%	14%
Regression (ROC)	90%	87%

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

From the accomplished outcomes in this review, the proposed model of 5G and LTE Signal Range Sensing utilizing Deep Learning innovation was executed using MATLAB TOOL BOX, which works to extruct the spectral sensing signals sent through the 5G correspondence channel from high-power coordinated irregular commotion and obstruction waves. A digital correspondence framework was reproduced to inspect the OFDM digital tweak strategy for transmission over a 5G and LTE correspondence channel with recreated high-power custom AWGN and obstruction tests to test the recommended spectral sensing model using the deep learning CNN algorithm. The preparation aftereffects of the deep learning CNN algorithm used in the spectral sensing framework showed astounding outcomes in the abilities of recognizing spectral signs with high precision and having the option to recover tweaked waves communicated by 5G OFDM innovation with high proficiency that came to 91% with high concealment of commotion and impedance impacts. In this review, and through the got results for the proposed model innovation, we could survey the benefits and disadvantages, or what is called points of qualities and shortcomings to help the peruser with a last rundown and audit of the recommended model efficiecy, as outlined in Table 3 beneath.

Table 3: Benefits versus drawbacks of the suggested scheme.

The Suggested Model	Advantages	Drawbacks
5G and LTE Signal Spectrum Sensing using Deep Learning technology	Efficient Spectral Sensing with Deep Learning CNN Algorithm Regression of 92%	Difficulty of updating the signals with sudden and high power variations
	Efficient Deep Learning CNN algorithm training with accuracy=91%	Accumulated Processing time due to high computations.
	Acceptable Processing Delay	Complicated Structure
	Low Spectral Sensig Error = 9%	High cost

5. CONCLUSIONS

In this study, correspondence range responsiveness improvement was tested by applying blended deep learning methods, in which data cross-over was diminished with upgraded smart control. Utilizing mixture deep learning strategies, this study shows the huge difficulties presented by 5G transmissions in wise sensing of the LTE signal range and different data in 5G remote sensor networks. Way impediments are distinguished as the essential hindrance. The states of the correspondence framework were additionally considered while arranging the network and sensors for the fifth era. The reproduction aftereffects of the recommended model show excellent precision for spectral sensing with CNN/DL algorithm approach of 91% when contrasted with the consequences of the FFT strategy for 100 MHz transporter recurrence with 100 dB SNR of the AWGN chael commotion.

6. REFERENCES

1. S. Ramjee, S. Ju, D. Yang, X. Liu, A. E. Gamal, and Y. C. Eldar, "Fast deep learning for automatic modulation classification," arXiv preprint arXiv:1901.05850, 2019.

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

2. G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 4700–4708.
3. K. Tekbıyık, O¨ . Akbunar, A. R. Ekti, A. Go¨rc¸in, and G. K. Kurt, “COSINE: Cellular cOmmunication SIgNal datasEt,” 2020. [Online]. Available: http://dx.doi.org/10.21227/safr-gh59
4. R. Roberts, W. Brown, and H. Loomis, “Computationally efficient algorithms for cyclic spectral analysis,” IEEE Signal Process. Mag., vol. 8, no. 2, pp. 38–49, Apr. 1991.
5. M. Zhang, M. Diao, and L. Guo, “Convolutional neural networks for automatic cognitive radio waveform recognition,” IEEE Access, vol. 5, pp. 11 074–11 082, 2017.
6. M. D. Zeiler and R. Fergus, “Stochastic pooling for regularization of deep convolutional neural networks,” arXiv preprint arXiv:1301.3557, 2013.
7. F. Chollet et al., “Keras,” https://keras.io, 2015.
8. D. Cabric, S. M. Mishra, and R. W. Brodersen, “Implementation issues in spectrum sensing for cognitive radios,” in Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, vol. 1, 2004, pp. 772–776.
9. K. Tekbiyik, A. R. Ekti, A. Gorcin, G. K. Kurt, and C. Kececi, “Robust and fast automatic modulation classification with CNN under multipath fading channels,” in IEEE 91st Vehicular Technology Conference (VTC2020-Spring), 2020, pp. 1–6.
10. M. Kulin, T. Kazaz, I. Moerman, and E. D. Poorter, “End-to-end learning from spectrum data: A deep learning approach for wireless signal identification in spectrum monitoring applications,” IEEE Access, vol. 6, pp. 18 484–18 501, Mar. 2018.
11. S. Kokalj-Filipovic, R. Miller, and J. Morman, “AutoEncoders for training compact deep learning RF classifiers for wireless protocols,” arXiv preprint arXiv:1904.11874, 2019.
12. S. Rajendran, W. Meert, D. Giustiniano, V. Lenders, and S. Pollin, “Deep learning models for wireless signal classification with distributed lowcost spectrum sensors,” IEEE Trans. Cogn. Commun. Netw., vol. 4, no. 3, pp. 433–445, May. 2018.
13. N. Han, S. Shon, J. H. Chung, and J. M. Kim, “Spectral correlation based signal detection method for spectrum sensing in IEEE 802.22 WRAN systems,” in 8th International Conference Advanced Communication Technology, vol. 3, 2006, pp. 1765–1770.
14. A. Hazza, M. Shoaib, S. A. Alshebeili, and A. Fahad, “An overview of feature-based methods for digital modulation classification,” in Proc. Intl. Commun. Signal Process., and Their Applications, Mar. 2013.
15. S. Ramjee, S. Ju, D. Yang, X. Liu, A. E. Gamal, and Y. C. Eldar, “Fast deep learning for automatic modulation classification,” arXiv preprint arXiv:1901.05850, 2019.
16. G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 4700–4708
17. Ku¨rs¸at Tekbıyık, Ali Rıza Ekti, G¨unes¸ Karabulut Kurt, “ Spectrum Sensing and Signal Identification with Deep Learning based on Spectral Correlation Function”, This study has been supported by NPRP12S-0225-190152 from the Qatar National Research Fund (a member of The Qatar Foundation)., arXiv:2003.08359v4 [eess.SP] 28 Apr 2021
18. S. Haykin and P. Setoodeh, “Cognitive radio networks: The spectrum supply chain paradigm,” IEEE Trans. Cogn. Commun. Netw., vol. 1, no. 1, pp. 3–28, 2015.

Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No.02, Feb-Mar 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.42.11.29

19. J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. Soong, and J. C. Zhang, "What will 5g be?" IEEE J. Sel. Areas Commun., vol. 32, no. 6, pp. 1065–1082, 2014.
20. C. De Lima, D. Belot, R. Berkvens, A. Bourdoux, D. Dardari, M. Guillaud, M. Isomursu, E.-S. Lohan, Y. Miao, A. N. Barreto et al., "Convergent communication, sensing and localization in 6G systems: An overview of technologies, opportunities and challenges," IEEE Access, 2021.
21. T. Wild, V. Braun, and H. Viswanathan, "Joint design of communication and sensing for beyond 5G and 6G systems," IEEE Access, vol. 9, pp. 30 845–30 857, 2021.
22. A. Gorcin and H. Arslan, "Signal identification for adaptive spectrum hyperspace access in wireless communications systems," IEEE Commun. Mag., vol. 52, no. 10, pp. 134–145, 2014.
23. W. M. Lees, A. Wunderlich, P. Jeavons, P. D. Hale, and M. R. Souryal, "Deep learning classification of 3.5 GHz band spectrograms with applications to spectrum sensing," IEEE Trans. Cogn. Commun. Netw., 2019.
24. Z. Qin, X. Zhou, L. Zhang, Y. Gao, Y.-C. Liang, and G. Y. Li, "20 years of evolution from cognitive to intelligent communications," IEEE Trans. Cogn. Commun. Netw., vol. 10, no. 1, pp. 6–20, Mar. 2020.
25. W. A. Gardner, "Exploitation of spectral redundancy in cyclostationary signals," IEEE Signal Process. Mag., vol. 8, no. 2, pp. 14–36, Apr. 1991.
26. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-air deep learning based radio signal classification," IEEE J. Sel. Signal Process., vol. 12, no. 1, pp. 168–179, Jan. 2018.