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Compact automatic modulation recognition using over-the-air signals and FOS features

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ABSTRACT

The recent deployment of automatic modulation recognition (AMR) for cognitive radio (CR) systems has significantly enhanced spectrum sensing capabilities. The utilization of real-time over-the-air digital radio frequency (RF) data for the development of a digital spectrum sensing model based on the automatic modulation classification (AMC) is presented in this study as a step for incorporating opportunistic spectrum sensing onto the NomadicBTS architecture. Some digital modulation techniques were studied for second-generation (2G) through fourth-generation (4G) technology. The raw RF signal dataset was digitized and curated, while non-complex first-order statistical (FOS) features were used with algorithms based on the Scaled conjugate gradient (SCG) and Levenberg-Marquardt (LM) to find the best learning algorithm for the generated AMR model. The results show that the developed AMR model has a very high likelihood of correctly classifying signals, with distinct patterns for each of the features of FOS. The results are compared to reveal a least mean square error (MSE) of 0.0131 with a maximum accuracy of 93.5 percent when the model was trained with seventy (70) neurons in the hidden layer using the LM method. The best model's accuracy will allow for the most precise identification of spectrum holes in the bands under consideration.

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1. INTRODUCTION

Globally, mobile phone usage and voice and data traffic are surging. Recent figures suggest that global growth will accelerate [1]. Like electricity, wireless communication is increasingly essential for most social, economic, and industrial activities. Due to this global trend, demand for faster data rates will grow, requiring more radio spectrum use. However, the radio spectrum is a limited natural resource controlled by National Regulatory Authorities (NRA) [2]. As spectrum use rises, a shortage appears and this is traceable to the inherent shortcomings of the conventional fixed spectrum access (FSA) used in most countries [3]. Based on an analysis of spectrum utilization and coverage internationally, the FSA policy won't be able to accommodate the growth of mobile connection and increased data transmission speeds in the coming years. To enhance QoS and user experience, more comprehensive and scalable spectrum access is needed, enabling users of more crowded channels to utilize available and less occupied channels seamlessly. Dynamic spectrum access (DSA) is a flexible spectrum policy linked with the IEEE 802.22 standard, and cognitive radio (CR) is required for DSA implementation.

Based on the CR definition as detailed in [4]–[7], a transceiver in a CR system can automatically identify the available spectrum and then use the vacant channels while skipping the occupied ones. It optimizes limited radio resources while causing the least amount of disturbance to main and secondary users, while DSA frees up idle capacity in occupied but underutilized bands such as TV white space [8]. While other functions play their roles, spectrum sensing is the most essential and remains the most fundamental component of CR's operation [9]. Several traditional approaches or algorithms for CR spectrum sensing are well-documented and frequently used [10], while machine learning (ML) algorithms are cutting-edge ways to improve CR system performance. They use the classification concept to detect the availability of frequency channels [11]. Automatic modulation recognition (AMR)-based spectrum sensing has gained scientific attention in recent years. It's an automated approach for recognizing signals' modulation classification and features [12], based on the concept that primary users (PUs) use a defined modulation technique for transmission within a given frequency channel. The absence of almost any modulation scheme in the channel means it's free and safe for transmission by a secondary user (SU) [13].

A wide variety of AMR techniques for spectrum sensing have been developed in literature and are classified into two major categories: (i) likelihood-based (LB) and (ii) feature-based (FB) techniques. LB approaches use hypothesis testing theory, and even though the performance is adjudged optimal, they are prone to high computation complexity. FB methods were created for practical application and typically extract features after preprocessing, employing classifiers to accomplish modulation classification. Various feature parameters could also be utilized to distinguish between multiple digital signals [14], [15]. The FB technique is further subdivided into shallow and deep learning techniques [12]. Although shallow machine learning-based classifiers have been used successfully, manual feature engineering relies on professional expertise, which may impair performance. Deep learning-based techniques for AMR have been presented due to their essential self-learning capabilities, especially when presented with an unfamiliar environment [16].

Interestingly, important studies on Feature-based AMR spectrum sensing have been documented in the literature. However, the majority of the studies that investigated AMR for spectrum sensing in CR used a variety of simulated datasets and feature types, such as constellation shapes, pseudo wigner-ville distribution (PWVD) coefficients, fractional lower-order statistics, and higher-order statistics [17]-[24], with only a few reports on results based on real datasets [13], [25]. Simulated datasets are not subjected to signal degradation effects, which normally occur in real-time wireless communication scenarios. Thus, models that are based on such datasets will have limited performance in real-time deployment. In addition, the use of complex feature extraction techniques will attract substantial computational costs.

In the present study, real-time over-the-air radio frequency (RF) datasets were collected, curated, and non-complex first-order statistical characteristics were used to create an AMR model. As a first step toward adding opportunistic spectrum sensing to the recently developed nomadic base transceiver station (NomadicBTS), a new base station architecture based on software-defined radio (SDR) technology for CR applications, this study describes the use of real-time over-the-air digital RF data for the development of a digital spectrum sensing model based on the automatic modulation classification (AMC), while exploring selected digital modulations.

2. METHOD

The nomadic base transceiver station (NomadicBTS) proposed in [26] is designed and built essentially on the software defined radio (SDR). The NomadicBTS architecture has two vital sub-modules with the front-end housing the SDR hardware while the SDR software operates on a personal computer (PC) at the back-end [26]. The architecture was extended in our study reported in [27] by incorporating CR capability with the AMR-based spectrum sensing model in the NomadicBTS architecture, where four (4) modulation schemes were considered and employed, namely, amplitude modulation (AM), Gaussian minimum shift key (GMSK), frequency modulation (FM) and (iv) noise (no-modulation).

In the current study, however, the following modulation schemes were evaluated to further advance the AMR model in the NomadicBTS architecture for real-time over-the-air digital RF signals: (i) quadrature phase shift keying (QPSK), (ii) Gaussian minimum shift keying (GMSK), (iii) binary phase shift keying (BPSK), (iv) eight-ary phase shift keying (8PSK), (v) 16-quadrature amplitude modulation (16-QAM), and

(vi) 64-quadrature amplitude modulation (64-QAM). A no-modulation signal (noise) was also incorporated to depict spectrum possibilities or gaps in a real-world situation. As seen in Figure 1, the model in this paper is classified into seven categories (modulation plus no-modulation). With the implementation of this model in the NomadicBTS architecture [26], [27] for practical deployment, it will be able to differentiate between occupied and vacant spectrum bands. It will also indicate the type of modulation scheme for an appropriate choice of demodulation algorithm, which enables adaptability across wireless standards in an SDR scenario. This is crucial given the widespread usage of SDRs in modern wireless communication systems alongside satellite, spectrum sensing, and cellular systems [26]-[29]. The following sections describe the phases involved in implementing the AMR model in this study. If any modulation scheme associated with any 2G to 4G communication technology is detected, it indicates the occupied states of the spectrum band. If, however, only the noise is detected, it indicates the availability (free) state of the spectrum band.

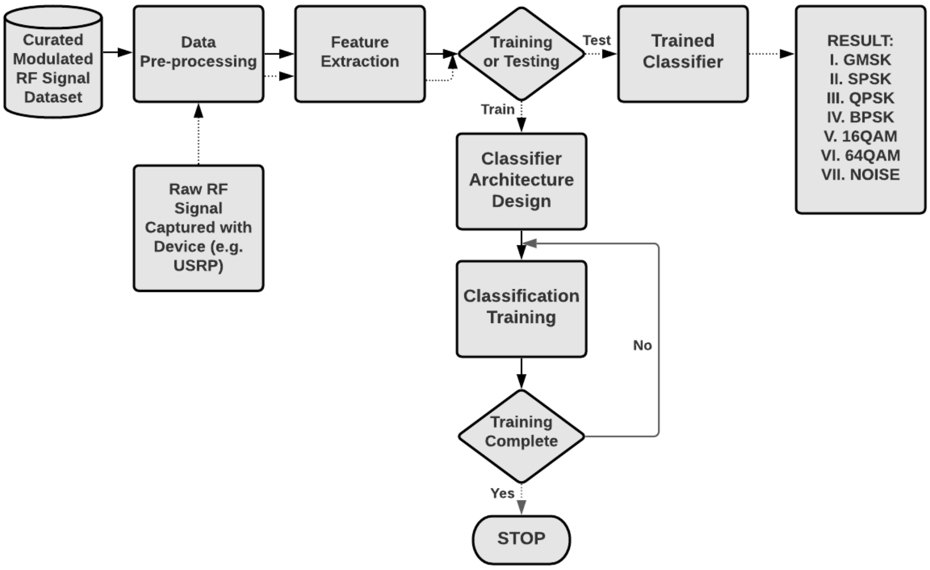


Figure 1. Flowchart for AMC-based spectrum sensing model development

2.1. Real-time RF data acquisition

For this study, raw RF signals for frequencies matching the specified modulation schemes were recorded between 2G to 4G cellular standards and WiFi (see Table 1). The data acquisition campaign was carried out at Covenant University, Ota, Ogun State, Nigeria (Figure 2), a Smart Campus with coverage for all the itemized wireless standards in Table 1. The real-time RF dataset was obtained from the setup comprising the Universal Software Radio Peripheral (USRP B200) as the hardware and the GNU-Radio Companion (GRC) as the software configured on Ubuntu Linux 16.04 LTS as the operating system (OS). This setup allows the USRP to effectively communicate with the host computer as shown in Figure 3. The technical and operating parameters of the USRP B200 are detailed in [27], while the parameter configurations for the different modulation schemes in this study are presented in Table 2. Each class had 50 real-time signals gathered, resulting in a total of 350 samples.

Table 1. Mobile technologies and respective modulation schemes [30]

Communications technology	Wireless generation	Centre frequency (MHz)	Modulation scheme
Global System for Mobile Communications (GSM)	2G	900, 1800	GMSK
General Packet Radio Service (GPRS)	2.5G	900, 1800	GMSK
Enhanced Data Rate for Global Evolution (EDGE)	2.75G	900, 1800	8PSK
Universal Mobile Telecommunications System (UMTS)	3G	900, 2100	QPSK
High Speed Packet Access (HSPA)	3.5G	2100	QPSK, 16-QAM
Long Term Evolution (LTE)	4G	700, 800, 1800, 2300, 2600	QPSK, 16-QAM, 64-QAM
Wireless Fidelity (Wi-Fi /WLAN)		2400, 5000	BPSK, QPSK, 16-QAM, 64-QAM

Figure 2. Location of one of the base stations for GSM data acquisition (latitude 6.6658^{O} N, longitude 3.1588^{0} E)

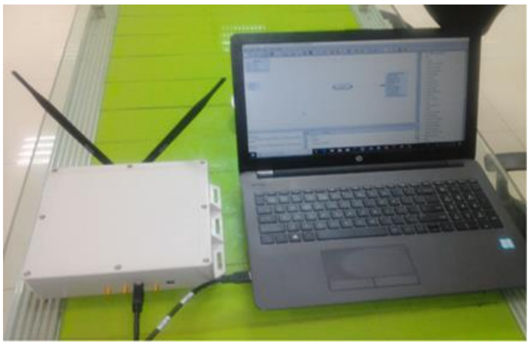


Figure 3. Interconnection of USRP B200 with host PC for real data acquisition campaign

Table 2. Parameter configurations for the modulation schemes in this study

Modulation scheme	Wireless standard	Bandwidth (kHz)	Operator	Downlink frequency range (MHz)	Centre frequency (MHz)
GMSK	GSM - 2G	200	Globacom	945-950	947.5
	GPRS – 2.5G		MTN	950-955	952.5
8PSK	EDGE – 2.75G	200	Airtel	955-960	957.5
QPSK	UMTS – 3G	5	MTN	2,110-2,120	2115
	LTE – 4G				

Although BPSK, 16 QAM, and 64 QAM, as well as QPSK are deployed in WiFi, they differ in terms of received signal strength indicator (RSSI) sensitivity and data rate. Table 3 shows the theoretical data ranges and minimum RSSI sensitivities for each of the modulation schemes in WiFi. The dataset for this study is available at the Advanced Signal Processing and Machine Intelligence Research (ASPMIR) Laboratory, Covenant University, Ota, Nigeria. To carry out an accurate signal acquisition for each of the WiFi modulation schemes during our campaign, strategic locations within the Covenant University campus were selected through the use of Network Signal Information Pro mobile application software. The software interface as shown in Figure 4 shows the parameters in Table 3 and other information about any WiFi access point (AP) that is enabled and connected. Real signals were captured at the location where the network information corresponded with the data rate range and minimum RSSI of any of the modulation schemes, as detailed in Table 3.

Table 3. Theoretical data rates and minimum RSSI sensitivities for the WiFi modulation schemes

Modulation scheme	Theoretical data rate (Mbps)	RSSI (dBm) for 20-MHz channel BW	RSSI (dBm) for 40-MHz channel BW
BPSK	6.50 – 7.20	-82	-79
QPSK	13.00 – 21.70	-79 to -77	-76 to -74
16-QAM	26.00 – 43.30	-74 to -70	-71 to -67
64-QAM	52.00 – 72.20	-66 to -64	-63 to -61

Figure 4. Network signal info pro with WiFi parameters

2.2. Data preprocessing

Each signal acquired at a particular frequency was digitized by the USRP B200 circuitry, which was used to realize the RF front-end of the NomadicBTS architecture. The received signal passes through different stages at the front end, such as: (i) filtering, (ii) down-conversion, (iii) signal conditioning, (iv) analog-to-digital conversion (ADC), and (v) digital signal processing (DSP) to produce the digitized format of the RF signal. The digitized signals were stored as .dat files in the GRC flow graph. Each of these binary files was further preprocessed into a vector of float numbers. Algorithm below shows data conversion algorithm, which outlines the procedure for converting each .dat file into a float vector. The algorithm was implemented with MATLAB R2017a.

```
Input: K, M
    K is the number of .dat files for each modulation class
    M is the number of modulation classes, each being represented by a separate directory
Output: K
    K represents the number of saved .mat files representing the corresponding .dat files

Clear the workspace
for all i = 1, 2, ….., M do
  Enable directory containing the .dat files to be opened
  for all j = 1, 2, ……, K do
     Use fopen('FileName') to get file identifier f_id
     If (f_id >= 3)
       Declare a float vector X
       Use fread(fid) to extract the file in vector form stored in X
       Save the data vector X as a MATLAB file with .mat extension
    Else
       Check the current directory and change it to the directory containing the desired
       file OR save the desired file into the directory.
  end if
  end for
end for
Stop
```

2.3. First-order statistical features

In this work, First-order statistics (FOS) values were retrieved for all preprocessed signal samples. For the following reasons, FOS features were considered and employed in this study: (i) the ability to identify distinctive attributes of signals, (ii) the awareness of signal modulation types, (iii) lack of sensitivity to variations in signal-to-noise ratio (SNR), and (iv) the significantly lower complexity compared to higher-order statistics based on our ultimate goal of achieving an on-device deployment of the AMR model [31]. The statistical parameters used are mean, variance, standard deviation, kurtosis, skewness, root mean square (RMS), median, and entropy, with mathematical details in [32]. The algorithm for the feature extraction procedure in this study is detailed in Algorithm below shows feature extraction algorithm, and its implementation was carried out in the MATLAB 2017a environment.

```
Input: K, M
    K is the number of .mat files saved for each modulation class.
    M is the number of directories where the .mat files are saved. Each directory represents a
    modulation class.
Output: The features to be extracted from each .mat file.

Clear the workspace
for all i = 1, 2, ….., M do
    Enable directory containing the .mat files to be loaded
    for all j = 1, 2, ……, K do
        If (.mat file = "saved")
            Load the .mat file in the workspace to enable vector X
            Get the mean feature of X using mean(X)
            Get the variance feature of X using var(X)
            Get the standard deviation feature of X using std(X)
            Get the skewness feature of X using skewness(X)
            Get the kurtosis feature of X using kurtosis(X)
            Get the root mean square feature of X using rms(X)
            Get the entropy feature of X using entropy(X)
            Get the median feature of X using median(X)
            Save these features for the sample in Excel spreadsheet
        Else
            Repeat the steps outlined in Algorithm 1 and save the extracted float file as .mat
            file in the appropriate directory.
    end if
  end for
end for
Stop
```

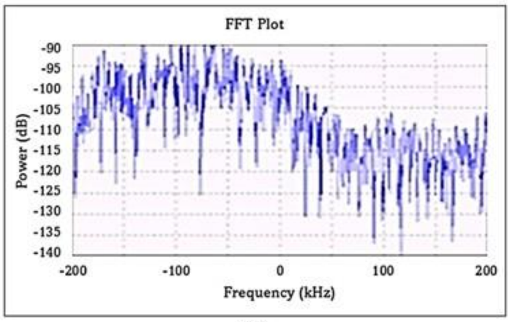
2.4. Development of a classification model

This involves building and training classification model configurations to differentiate between the seven classes, which are the six modulation schemes and a no-modulation output as noise. Multiple experiments were conducted utilizing two classification models: kernel-based SVM and multilayer perceptron ANN (MLP-ANN). The experiments employed the following MLP-ANN model specifications:

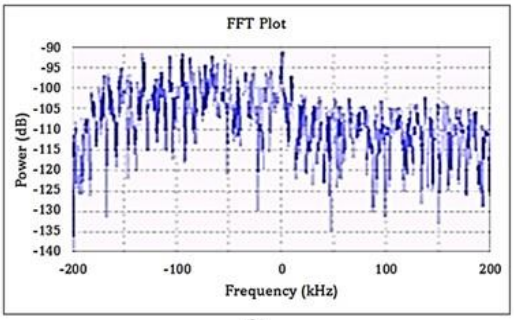
a. Architecture type: a feed-forward MLP-ANN with an input layer of 8 neurons showing characteristics, experimentally varying hidden layer neurons, and an output layer of 7 neurons for 7 modulation classes [13].
b. Activation functions: in the input layer, a linear activation function, i.e., Purelin, was utilized. In addition, to incorporate non-linearity into the network, the bipolar sigmoidal function, i.e., the Tan-Sigmoid function, was applied to both the hidden layer and the output layer [13].
c. Learning algorithms: to train the model, two variants of back propagation algorithms were employed: the Levenberg-Marquardt (LM) and the scaled conjugate gradient (SCG). They were chosen based on their training speed, efficiency, stability, and superior accuracy [13], [29].
d. Performance functions: to evaluate training performance, the mean square error (MSE) and accuracy were utilized.

3. RESULTS AND DISCUSSION

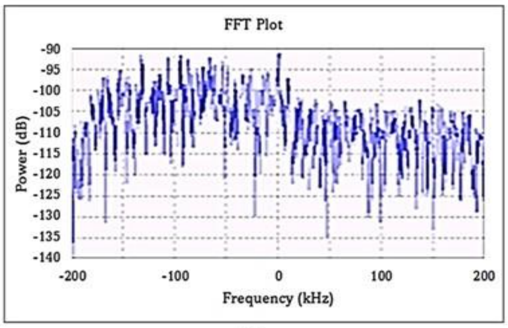
For the development of the AMR model, different classification model configurations were used to differentiate between the seven classes. Several experiments were carried out to find the best model for this objective using the kernel-based SVM and the MLP-ANN classification models. For the type of architecture, a feed-forward MLP-ANN was set up, and Purelin was utilized as the linear activation function. Non-linearity was incorporated into the network, and the Tan-Sigmoid function was applied to the hidden and output layers. The LM and SCG algorithms were employed for the training of the model. The performance was evaluated using the mean square error (MSE), while the accuracy was established using the confusion matrix and the popular receiver operator characteristics (ROC) methodology. Figures 5(a)-(g) depict some spectrum graphs as samples of the raw RF signals obtained. These charts were developed and presented on the FFT sink in the GRC environment.



(a)



(b)



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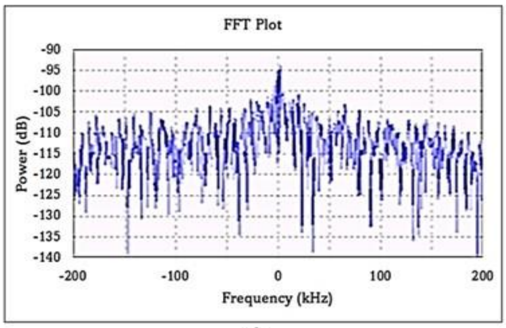

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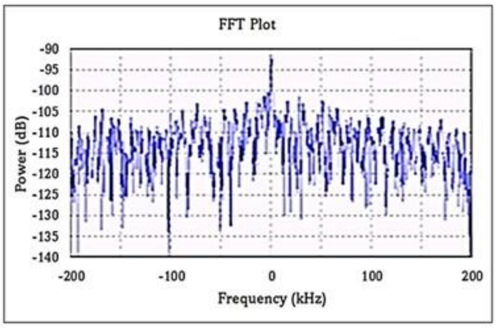
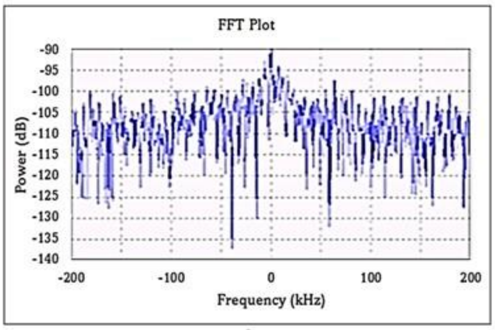
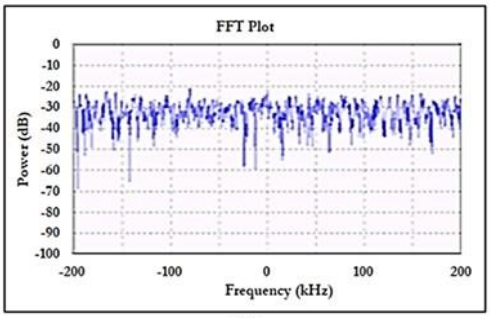


(e)



(f)



(g)

Figure 5. Spectrum plots for (a) sample of GMSK signals, (b) sample of 8PSK signals, (c) sample of QPSK signals (d) sample of BPSK signals (e) sample of 16 QAM signals (f) sample of 64QAM signals and (g) sample of no-modulation signals

Figures 6(a)-(g) present bar charts demonstrating the retrieved FOS attributes for each class. This means that the created AMR model is highly likely to classify signals correctly. On the horizontal plane of the graph, the FOS is denoted by the mean, standard deviation, variance, skewness, RMS, kurtosis, median, and entropy. As illustrated, the pattern for each of the FOS attributes for the different class are distinct, which is a vital element for pattern recognition using the AMR technique. The LM and SCG algorithms were used to determine the best learning algorithm for the AMR model developed. The number of neurons in the hidden layer was varied for each learning algorithm in order to systematically ascertain the number of hidden layer neurons that generated low MSE with the highest accuracy.

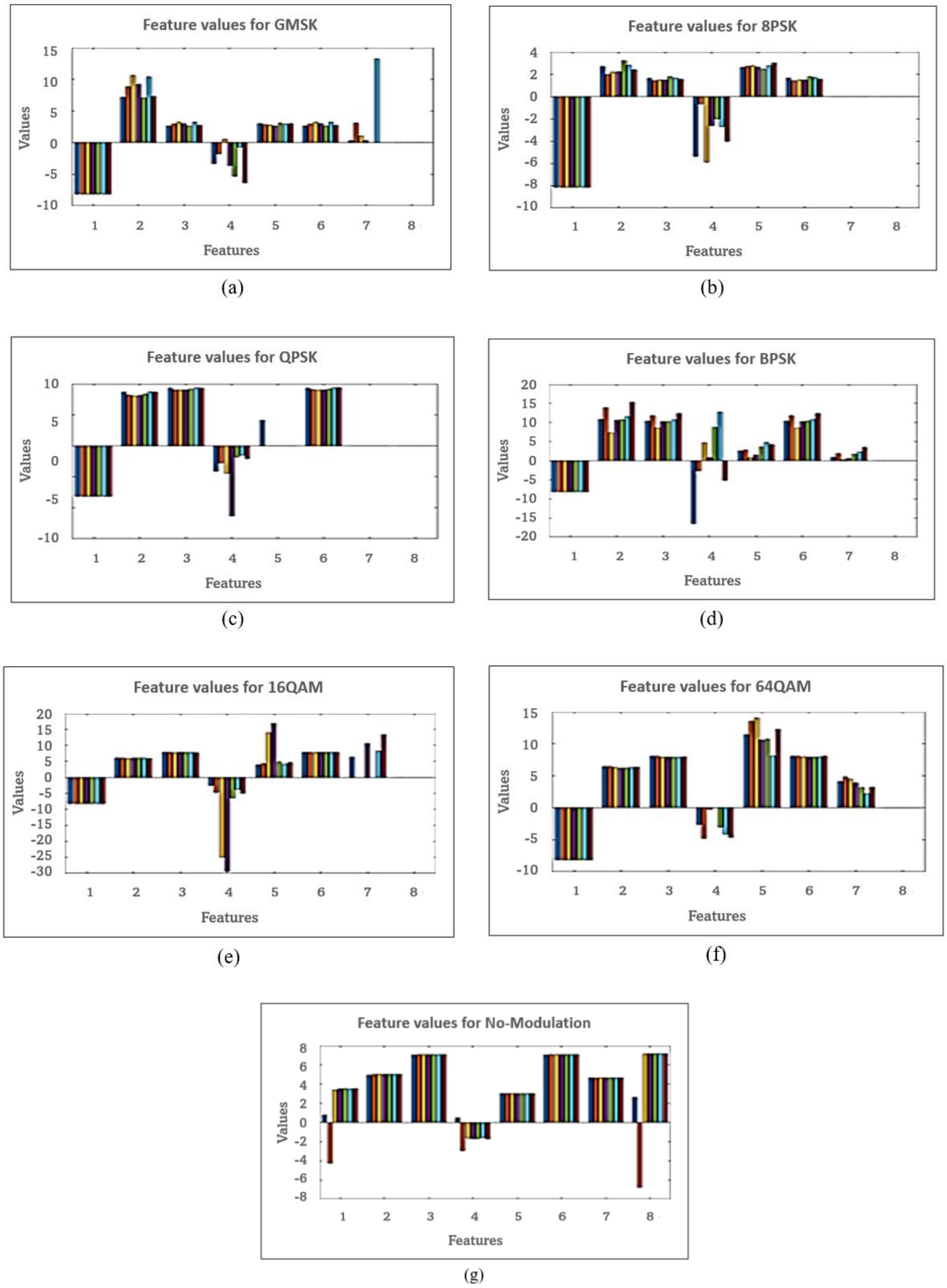


Figure 6. feature bar charts for (a) GMSK sample (b) 8PSK sample (c) QPSK sample (d) BPSK sample (e) 16-QAM sample (f) 64-QAM sample and (g) noise sample

Based on the comparison of the findings, with seventy (70) neurons in the hidden layer, the model had the lowest MSE of 0.0131 and the highest accuracy of 93.5 percent when trained using the LM algorithm. Additionally, it was observed that when training using LM repeatedly on a predefined number of neurons for the hidden layer, the obtained accuracy values were relatively steady and within a very suitable range. As for the SCG, however, the levels of accuracy acquired for each predefined number of neurons for the hidden layer diverged virtually inexplicably. Figures 7 and 8 represent the best AMR model's confusion matrix and ROC curves, respectively, from this study. This model's specifications are shown in Table 4, and its topology is shown in Figure 9. The optimal AMR model obtained in this study is based on the compact FOS features that will form a CR component for the real-time deployment of NomadicBTS architecture to achieve dynamic spectrum sensing [26]. Similar efforts on the use of statistical features and CR for spectrum sensing have also been reported in the literature [27]-[29].

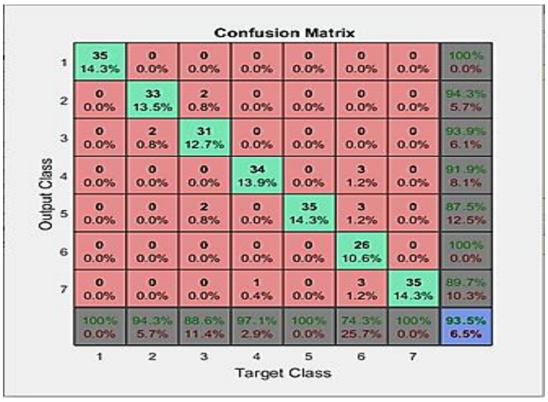


Figure 7. Confusion matrix for 70 hidden-Layer neurons for the LM-trained model

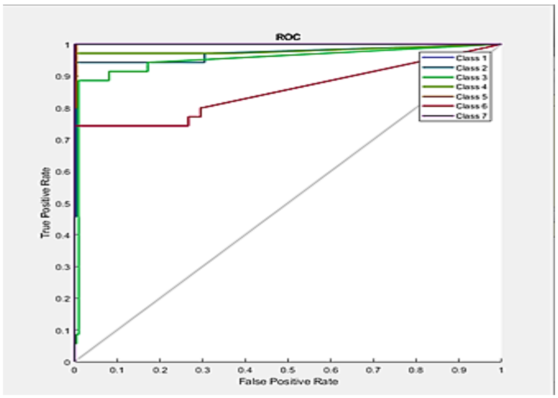


Figure 8. ROC curves for the 70 hidden-layer neurons in the LM-trained model

The accuracy confusion matrix for the proposed model is presented in Figure 7. As shown, most of the various modulation signal types are classified correctly with a 93.5% accuracy rate. This result indicates that the proposed model demonstrates an acceptable classifying capability for various modulation signals. As shown in Figure 8, the area under the curve (AUC) metric was used to evaluate the overall test accuracy of the optimal model by plotting the output probabilities based on the ROC methodology for the seven (7) different modulation classes. It is generally observed that the model performed satisfactorily well, with classes 1, 5, and 7 recording the highest AUC, followed by classes 2, 3, and 4, while class 6 is identified with the least AUC.

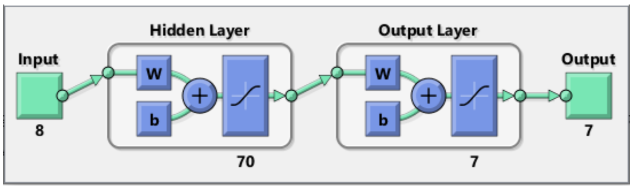


Figure 9. Topology of the best AMR model

Table 4. Characteristics of the best AMR model

Characteristics	Description
Number of neurons at the input layer	8
Number of neurons at the hidden layer	70
Number of neurons at the output layer	7
Input layer's activation function	Purelin
Hidden layer's activation function	Tan-sigmoid
Output layer's activation function	Tan-sigmoid
Mean square error (MSE)	0.0131
Accuracy	93.5%
Learning algorithm	Levenberg-Marquardt (LM)

4. CONCLUSION

Presented here is the development of an AMR-based spectrum sensing model toward the implementation of opportunistic spectrum sensing into the NomadicBTS architecture. Real-time over-the-air RF datasets were gathered from the experimental setup, including the USRP B200 device and the GRC software, and non-complex first-order statistical features were used as descriptors to design the AMR model. Selected digital modulation techniques for second-generation (2G) through fourth-generation (4G) technologies were evaluated, and the accuracy of the best model was determined. This would inevitably improve the identification of spectral holes within the reviewed bands. Complete prototyping of the CR-based NomadicBTS architecture (incorporating the AMR model for the fifth generation (5G) mobile technologies), interoperability of multiple NomadicBTS for cooperative spectrum sensing, development of deep learning-based AMR models with more digital modulation schemes, and prototyping of the architecture for other use cases are all exciting areas for further research.

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REFERENCES

[1] R. De', N. Pandey, and A. Pal, "Impact of digital surge during Covid-19 pandemic: A viewpoint on research and practice," *Int. J. Inf. Manage.*, vol. 55, p. 102171, Dec. 2020, doi: 10.1016/J.IJINFOMGT.2020.102171.

[2] S. Ziafat, W. Ejaz, and H. U. Jamal, "Spectrum sensing techniques for cognitive radio networks: Performance analysis," *2011 IEEE MTT-S International Microwave Workshop Series on Intelligent Radio for Future Personal Terminals*, 2011, pp. 1-4, doi: 10.1109/IMWS2.2011.6027191.

[3] F. Javed, A. Mahmood, I. Shafi, and S. Ali, "Open Research Areas in Cognitive Radios," in 2012 Fourth International Conference on Computational Intelligence, Modelling and Simulation, 2012, pp. 375–380, doi: 10.1109/CIMSim.2012.40.

[4] A. M. Fanan, N. G. Riley, M. Mehdawi, M. Ammar, and M. Zolfaghari, "Survey: A comparison of spectrum sensing techniques in cognitive radio," in *Int'l Conference Image Processing, Computers and Industrial Engineering (ICICIE)*, 2014, pp. 15–16, doi: 10.15242/iie.e0114560.

[5] L. Duan, L. Gao, and J. Huang, "Contract-based cooperative spectrum sharing," *2011 IEEE Int. Symp. Dyn. Spectr. Access Networks, DySPAN*, pp. 399–407, 2011, doi: 10.1109/DYSPAN.2011.5936229.

[6] F. Lin *et al.*, "Cognitive radio network as wireless sensor network (II): Security consideration," in Proceedings of the 2011 IEEE National Aerospace and Electronics Conference (NAECON), 2011, pp. 324–328, doi: *10.1109/NAECON.2011.6183125*.

[7] R. C. Qiu *et al.*, "Cognitive Radio Network for the Smart Grid: Experimental System Architecture, Control Algorithms, Security, and Microgrid Testbed," *IEEE Trans. Smart Grid*, vol. 2, no. 4, pp. 724–740, 2011, doi: 10.1109/TSG.2011.2160101.

[8] D. Corral-De-Witt *et al*., "Sensing TV spectrum using Software Defined Radio hardware," in *2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE)*, 2017, pp. 1–4, doi: 10.1109/CCECE.2017.7946840.

[9] S. Pattanayak, P. Venkateswaran, and R. Nandi, "Artificial neural networks for cognitive radio: A preliminary survey," in *2012 International Conference on Wireless Communications, Networking and Mobile Computing, WiCOM 2012*, 2012, pp. 1–4, doi: 10.1109/WiCOM.2012.6478438.

[10] M. Mourad and A. Hussein, "Major Spectrum Sensing Techniques for Cognitive Radio Networks: A Survey," *Int. J. Eng. Innov. Technol.*, vol. 5, no. 3, pp. 24 – 37, 2015, doi: 10.17605/OSF.IO/TWUXM.

[11] Y. Arjoune and N. Kaabouch, "A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions," *Sensors*, vol. 19, no. 1, p. 126, 2019, doi: 10.3390/s19010126.

[12] B. Ramkumar, "Automatic modulation classification for cognitive radios using cyclic feature detection," *IEEE Circuits Syst. Mag.*, vol. 9, no. 2, pp. 27–45, 2009, doi: 10.1109/MCAS.2008.931739.

[13] J. J. Popoola and R. Van Olst, "The performance evaluation of a spectrum sensing implementation using an automatic modulation classification detection method with a Universal Software Radio Peripheral," *Expert Syst. Appl.*, vol. 40, no. 6, pp. 2165–2173, 2013, doi: 10.1016/j.eswa.2012.10.047.

[14] A. K. Ali and E. Erçelebi, "Automatic modulation classification using different neural network and PCA combinations," *Expert Syst. Appl.*, vol. 178, p. 114931, Sep. 2021, doi: 10.1016/j.eswa.2021.114931.

[15] M. L. D. Wong and A. K. Nandi, "Automatic digital modulation recognition using artificial neural network and genetic algorithm," *Signal Processing*, vol. 84, no. 2, pp. 351–365, Feb. 2004, doi: 10.1016/j.sigpro.2003.10.019.

[16] X. Li, F. Dong, S. Zhang, and W. Guo, "A Survey on Deep Learning Techniques in Wireless Signal Recognition," *Wirel. Commun. Mob. Comput.*, vol. 2019, 2019, doi: 10.1155/2019/5629572.

[17] M. Derakhtian, A. A. Tadaion, and S. Gazor, "Modulation classification of linearly modulated signals in slow flat fading channels," in *IET Signal Processing*, 2011, vol. 5, no. 5, pp. 443–450, doi: 10.1049/iet-spr.2009.0298.

[18] S. Sichelschmidt and D. Bruckmann, "Performance optimization of Automatic Modulation Classification for different signal and channel types," in *2012 IEEE International Conference on Wireless Information Technology and Systems, ICWITS*, 2012, pp. 1–4, doi: 10.1109/ICWITS.2012.6417709.

[19] O. Azarmanesh and S. G. Bilén, "I-Q diagram utilization in a novel modulation classification technique for cognitive radio applications," *Eurasip J. Wirel. Commun. Netw.*, vol. 2013, no. 1, pp. 1–12, 2013, doi: 10.1186/1687-1499-2013-289.

[20] A. Elrharras, R. Saadane, M. Wahbi, and A. Hamdoun, "Signal detection and automatic modulation classification based spectrum sensing using PCA-ANN with real word signals," *Appl. Math. Sci.*, vol. 8, no. 157–160, pp. 7959–7977, 2014, doi: 10.12988/ams.2014.49736.
[21] T. Zare and J. Abouei, "Kernel-based Generalized Discriminant Analysis for signal classification in cognitive radio," in *2014 7th International Symposium on Telecommunications*, IST 2014, 2014, pp. 1106–1112, doi: 10.1109/ISTEL.2014.7000869.
[22] X. Wang, J. Wang, Z. Liu, X. Song, and X. Hu, "A Novel Signal Identification Method via Improved Random Forest in Cognitive Network," *Int. J. Signal Process. Image Process. Pattern Recognit.*, vol. 9, no. 3, pp. 133–142, 2016, doi: 10.14257/ijsip.2016.9.3.12.
[23] X. Zhu and T. Fujii, "A novel modulation classification method in cognitive radios based on features clustering of time-frequency," in *IEEE Radio and Wireless Symposium, RWS*, 2016, vol. 2016-March, pp. 57–59, doi: 10.1109/RWS.2016.7444364.
[24] S. Peng, H. Jiang, H. Wang, H. Alwageed, and Y. D. Yao, "Modulation classification using convolutional Neural Network based deep learning model," in *2017 26th Wireless and Optical Communication Conference (WOCC)*, 2017, pp. 1–5, doi: 10.1109/WOCC.2017.7929000.
[25] N. Madhavan, A. P. Vinod, A. S. Madhukumar, and A. K. Krishna, "Spectrum sensing and modulation classification for cognitive radios using cumulants based on fractional lower order statistics," *AEU - Int. J. Electron. Commun.*, vol. 67, no. 6, pp. 479–490, 2013, doi: 10.1016/j.aeue.2012.11.004.
[26] E. Adetiba, V. O. Matthews, S. N. John, S. I. Popoola, and A. Abayomi, "NomadicBTS: Evolving cellular communication networks with software-defined radio architecture and open-source technologies," *Cogent Eng.*, vol. 5, no. 1, pp. 1–15, 2018, doi: 10.1080/23311916.2018.1507465.
[27] F. J. Olaloye and E. Adetiba, "Dynamic Spectrum Sensing with Automatic Modulation Classification for a Cognitive Radio Enabled NomadicBTS," *J. Phys. Conf. Ser.*, vol. 1378, no. 4, 2019, doi: 10.1088/1742-6596/1378/4/042092.
[28] S. Ajala, E. Adetiba, M. B. Akanle, O. O. Obiyemi, S. Thakur, and J. Abolarinwa, "Experimentations on the Transmit Power of a Universal Software Radio Peripheral Using GNU Radio Framework and a Handheld RF Explorer," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 655, no. 1, p. 012006, Feb. 2021, doi: 10.1088/1755-1315/655/1/012006.
[29] M. A. Sarijari, A. Marwanto, N. Fisal, S. K. S. Yusof, R. A. Rashid, and M. H. Satria, "Energy detection sensing based on GNU radio and USRP: An analysis study," in *Proceedings - MICC 2009: 2009 IEEE 9th Malaysia International Conference on Communications with a Special Workshop on Digital TV Contents*, 2009, pp. 338–342, doi: 10.1109/MICC.2009.5431525.
[30] G. Goedhart *et al.*, "Using software-modified smartphones to validate self-reported mobile phone use in young people: A pilot study," Bioelectromagnetics, vol. 36, no. 7, pp. 538–543, 2015, doi: 10.1002/bem.21931.
[31] P. Shih and D. Chang, "An automatic modulation classification technique using high-order statistics for multipath fading channels," in *2011 11th International Conference on ITS Telecommunications*, 2011, pp. 691–695, doi: 10.1109/ITST.2011.6060143.
[32] E. Adetiba, V. C. Iweanya, S. I. Popoola, J. N. Adetiba, and C. Menon, "Automated detection of heart defects in athletes based on electrocardiography and artificial neural network," *Cogent Eng.*, vol. 4, no. 1, p. 1411220, 2017, doi: 10.1080/23311916.2017.1411220.

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