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An Intelligent Framework for Cellular Signal Identification Using Extreme Learning Machine

CH.Sravan Kumar[1], G.Niharika[2]
[1]Assistant Professor, Department of MCA, Megha Institute of Engineering and Technology for Women, Edulabad (Village), Ghatkesar (Mandal), Medchal District, Telangana –, India.
[2]MCA Student, Department of MCA, Megha Institute of Engineering and Technology for Women, Edulabad (Village), Ghatkesar (Mandal), Medchal District, Telangana –, India.

***Abstract* – Automatic identification of wireless communication signals is a fundamental capability of intelligent radio systems, enabling efficient spectrum utilization, interference management, network monitoring, and electronic surveillance. Conventional automatic signal identification (ASI) techniques, including likelihood-based and feature-based methods, often experience limitations associated with high computational complexity, sensitivity to channel variations, and reduced robustness under practical deployment conditions. Recent advances in machine learning have demonstrated significant potential for improving signal identification accuracy while reducing computational overhead. This study presents an Extreme Learning Machine (ELM)-based framework for the automatic identification of cellular signals using real Power Spectral Density (PSD) measurements collected over the air. The proposed methodology processes PSD measurements belonging to Global System for Mobile Communications (GSM), Universal Mobile Telecommunications System (UMTS), and Long-Term Evolution (LTE) networks by transforming PSD measurements into two-dimensional binary images through a PSD image-mapping process. Following preprocessing and image standardization, the generated signal images are supplied to an ELM classifier that utilizes randomly initialized hidden-layer parameters and analytically determined output weights to achieve rapid model training. The proposed model is evaluated using two independent datasets, DS1 and DS2, where DS1 is employed for hyperparameter optimization and DS2 is used to evaluate robustness and generalization capability. Experimental results demonstrate that the proposed ELM framework achieves high identification accuracy while significantly reducing training complexity compared with existing neural network approaches. These findings indicate that the proposed model provides an efficient and reliable solution for intelligent wireless communication systems requiring fast and accurate cellular signal identification.**

Keywords - **Cellular Signal Identification, Extreme Learning Machine (ELM), Machine Learning, Wireless Communication, Signal Classification, Radio Frequency (RF) Signals, Feature Extraction.**

I. INTRODUCTION

The continuous growth of wireless communication technologies has substantially increased the demand for efficient utilization of the limited radio frequency spectrum. Modern communication environments consist of numerous heterogeneous wireless systems operating simultaneously across multiple frequency bands, creating significant challenges in spectrum management, interference mitigation, signal monitoring, and intelligent resource allocation. As wireless networks continue to evolve, intelligent radio systems capable of automatically recognizing and analyzing communication signals have become increasingly important for both commercial and defense-related applications. These intelligent systems support dynamic spectrum access, cognitive radio operation, electronic warfare, network optimization, and real-time spectrum surveillance.

Automatic Signal Identification (ASI) represents one of the core functionalities of intelligent radio systems. The objective of ASI is to accurately determine the type of communication signal without requiring prior knowledge of the transmitting source. Conventional ASI techniques generally rely on likelihood-based or feature-based algorithms. Although likelihood-based methods often provide high classification accuracy, they require extensive mathematical computations and significant processing resources. Conversely, feature-based techniques reduce computational requirements but frequently experience performance degradation under noisy environments, channel distortions, and varying propagation conditions. These limitations have motivated researchers to investigate more robust data-driven approaches capable of maintaining reliable identification performance under practical wireless communication scenarios.

Recent developments in Machine Learning (ML) and Artificial Intelligence (AI) have transformed signal processing by enabling automatic extraction of discriminative features directly from measurement data. Deep learning models and neural network architectures have demonstrated considerable success in communication signal classification because they eliminate the need for manually designed feature extraction procedures. However, many conventional neural networks require iterative optimization using backpropagation, resulting in prolonged training time, increased computational complexity, and substantial hardware requirements. These challenges become more significant when real-time deployment and resource-constrained wireless systems are considered.

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To address these limitations, this study proposes an Extreme Learning Machine (ELM) framework for identifying cellular communication signals using real Power Spectral Density (PSD) measurements acquired over the air. The proposed system focuses on the automatic identification of three widely deployed cellular technologies: Global System for Mobile Communications (GSM), Universal Mobile Telecommunications System (UMTS), and Long-Term Evolution (LTE). Initially, the acquired PSD measurements are transformed into binary image representations through a dedicated PSD image-mapping process. These images subsequently undergo preprocessing and standardization before being supplied to the ELM classifier. Unlike conventional feedforward neural networks, the ELM randomly initializes the hidden-layer parameters while analytically computing the output-layer weights, thereby substantially reducing computational complexity and accelerating model training. The proposed framework is evaluated using two independent datasets, namely DS1 and DS2, to examine both classification performance and model generalization. DS1 is utilized to optimize model hyperparameters, whereas DS2, collected under different measurement conditions, assesses the robustness of the trained model without additional parameter tuning. The experimental analysis further includes computational complexity evaluation based on parameter complexity, multiplication complexity, and addition complexity, together with comparisons against existing neural network-based signal identification methods. The obtained results demonstrate that the proposed ELM framework provides highly accurate cellular signal identification while significantly reducing training complexity, making it an effective solution for intelligent radio applications and next-generation wireless communication systems.

II. LITERATURE SURVEY

Machine learning has become an important research direction for automatic signal identification (ASI) because of its capability to learn complex signal characteristics directly from communication measurements. Recent studies have investigated various deep learning and machine learning models to improve identification accuracy, reduce computational complexity, and enhance robustness under practical wireless communication environments. These techniques have demonstrated promising performance in identifying modulation schemes, cellular technologies, and radio frequency signals acquired from both simulated and real-world measurements.

Eldemerdash et al. investigated intelligent radio measurement systems capable of identifying cellular communication networks using signal processing techniques. Their research emphasized the importance of automatic signal identification for spectrum monitoring and cognitive radio applications, demonstrating that reliable signal recognition contributes significantly to intelligent spectrum management. However, the proposed approaches primarily relied on conventional feature extraction techniques that require substantial computational effort under complex communication environments.

Makled et al. proposed machine learning-based methods for identifying cellular signal measurements using real Power Spectral Density (PSD) data. Their studies demonstrated that neural network-based approaches outperform traditional signal identification algorithms by automatically learning representative signal characteristics directly from measurement data. The experimental results confirmed the feasibility of machine learning for identifying GSM, UMTS, and LTE signals while improving robustness against practical channel impairments. Nevertheless, conventional neural network training remains computationally intensive because of iterative backpropagation optimization.

Several researchers have explored Convolutional Neural Networks (CNNs) and hybrid neural network architectures for communication signal classification. Xia et al. employed CNN models to classify cellular signals under additive white Gaussian noise and Rayleigh fading channels, demonstrating improved feature extraction capability compared with traditional classification algorithms. Similarly, Makled et al. introduced a Hybrid Convolutional Feedforward Neural Network (HCFNN) for identifying cellular signal measurements from PSD images. Their model achieved excellent classification accuracy by combining convolutional feature extraction with feedforward neural network classification; however, the architecture required considerably higher computational resources and longer training times.

The development of Extreme Learning Machines (ELMs) has provided an alternative machine learning framework for rapid classification tasks. Huang et al. introduced the ELM architecture as a single-hidden-layer feedforward neural network that randomly initializes hidden-layer parameters while analytically determining output-layer weights. This training strategy eliminates iterative backpropagation, resulting in substantially faster learning and reduced computational complexity while maintaining strong generalization performance. Subsequent studies demonstrated the successful application of ELM models across pattern recognition, regression, and multiclass classification problems, highlighting their computational efficiency and robustness for large-scale datasets.

Although previous investigations have demonstrated the effectiveness of deep learning models, CNN architectures, and conventional feedforward neural networks for wireless signal classification, relatively limited research has focused on utilizing Extreme Learning Machines for identifying real cellular PSD measurements acquired under practical operating conditions. Furthermore, evaluating model robustness using independent datasets collected under different environmental conditions remains an

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important challenge for intelligent wireless communication systems. To address these limitations, the present study develops an ELM-based signal identification framework that converts PSD measurements into two-dimensional binary images before classification. The proposed approach is evaluated using two independent datasets (DS1 and DS2) and further analyzed through computational complexity assessment, demonstrating an effective balance between identification accuracy, computational efficiency, and practical deployment capability.

III. PROPOSED METHODOLOGY

The proposed system introduces an Extreme Learning Machine (ELM)-based framework for the automatic identification of cellular communication signals using Power Spectral Density (PSD) measurements collected from real wireless environments. The framework is designed to accurately classify three widely deployed cellular technologies, namely Global System for Mobile Communications (GSM), Universal Mobile Telecommunications System (UMTS), and Long-Term Evolution (LTE). Unlike conventional neural network approaches that require iterative backpropagation for parameter optimization, the proposed ELM classifier randomly initializes hidden-layer parameters while analytically determining the output weights, significantly reducing computational complexity and training time. The overall framework integrates signal acquisition, preprocessing, PSD image generation, feature representation, ELM-based classification, and performance evaluation into a unified automatic signal identification system.

The identification process begins with the acquisition of real Power Spectral Density (PSD) measurements using spectrum monitoring equipment. The collected measurements represent the spectral characteristics of GSM, UMTS, and LTE communication signals under practical wireless operating conditions. Since raw PSD measurements cannot be directly supplied to the classifier, the proposed framework first converts the one-dimensional PSD vectors into two-dimensional binary images using a dedicated PSD image-mapping algorithm. This transformation preserves the spectral distribution while generating a standardized image representation suitable for machine learning-based classification.

After image generation, the resulting PSD images undergo preprocessing to improve data consistency before model training. The preprocessing stage includes image normalization, resizing, and organization into separate training and testing datasets. Two independent datasets, DS1 and DS2, are employed throughout the experimental analysis. The DS1 dataset is utilized for hyperparameter selection and model optimization, whereas DS2, collected under different environmental conditions, is reserved for evaluating the robustness and generalization capability of the trained classifier. This dual-dataset evaluation strategy provides a comprehensive assessment of model performance under realistic deployment scenarios.

The processed PSD images are subsequently supplied to the Extreme Learning Machine (ELM) classifier. The ELM architecture consists of a single hidden-layer feedforward neural network in which the input layer receives the PSD image features, the hidden-layer parameters are randomly assigned, and the output weights are computed analytically using the Moore–Penrose generalized inverse. Because iterative gradient-based optimization is eliminated, the proposed classifier achieves extremely fast learning while maintaining high classification accuracy. This computationally efficient learning strategy enables rapid deployment in intelligent wireless communication systems that require real-time signal identification.

During model training, the ELM learns the relationship between the generated PSD image representations and their corresponding communication technologies. Once training is completed, the optimized classifier predicts whether an unknown PSD measurement belongs to GSM, UMTS, or LTE. Classification performance is evaluated using standard performance metrics together with computational complexity analysis. The experimental evaluation additionally compares the proposed ELM classifier with conventional neural network models by analyzing parameter complexity, multiplication complexity, and addition complexity, thereby demonstrating the computational advantages of the proposed framework.

Overall, the proposed system combines PSD image mapping, dataset preprocessing, Extreme Learning Machine classification, and computational complexity evaluation into an efficient automatic signal identification framework. The proposed methodology achieves reliable cellular signal recognition while maintaining significantly lower computational requirements than conventional deep learning models, making it suitable for applications involving cognitive radio, wireless spectrum monitoring, electromagnetic surveillance, dynamic spectrum access, and next-generation intelligent communication systems.

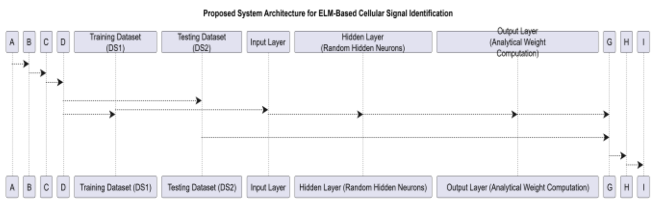

Fig. 1. System Architecture of the Proposed Extreme Learning Machine-Based Cellular Signal Identification Framework

IV. COMPUTATIONAL COMPLEXITY ANALYSIS

Computational efficiency is an important consideration for automatic signal identification systems, particularly when real-time spectrum monitoring and intelligent wireless communication applications are involved. Although deep neural networks often achieve excellent classification accuracy, their iterative optimization procedures require considerable computational resources, making deployment challenging for resource-constrained communication devices. Therefore, the proposed study evaluates the computational efficiency of the Extreme Learning Machine (ELM) by comparing its computational complexity with existing neural network-based classification approaches.

The computational complexity evaluation considers three major components:

- Parameter Complexity
- Multiplication Complexity
- Addition Complexity

Parameter complexity represents the total number of trainable parameters required by the classification model. Since the ELM randomly initializes hidden-layer parameters and analytically computes only the output-layer weights, the total number of trainable parameters is significantly lower than that of conventional deep neural networks employing iterative backpropagation.

Multiplication complexity evaluates the total number of multiplication operations required during both training and inference. Conventional multilayer neural networks repeatedly update parameters through gradient-based optimization, resulting in substantial multiplication overhead across multiple training epochs. In contrast, the proposed ELM performs a single analytical computation for output weight estimation, thereby considerably reducing multiplication operations while maintaining effective classification performance.

Similarly, addition complexity measures the number of addition operations executed during model computation. Because the ELM eliminates repeated parameter updates, the overall number of addition operations remains substantially lower than that required by traditional feedforward and convolutional neural network architectures. This reduction contributes directly to faster execution time and lower computational resource consumption.

To verify these advantages, the proposed ELM framework is experimentally compared with existing neural network classifiers using both DS1 and DS2 datasets. The complexity analysis demonstrates that the proposed model achieves competitive classification performance while requiring significantly fewer computational operations. Consequently, the ELM framework provides an attractive solution for intelligent communication systems that require rapid learning, low memory utilization, and efficient real-time implementation.

Overall, the computational complexity analysis confirms that the proposed Extreme Learning Machine successfully balances classification accuracy, training speed, and computational efficiency. The reduced parameter complexity together with lower multiplication and addition requirements makes the proposed framework particularly suitable for deployment in cognitive radio systems, software-defined radios, wireless spectrum monitoring platforms, and other intelligent communication environments where computational resources are limited.

V. FUTURE ENHANCEMENT

The proposed Extreme Learning Machine (ELM) framework demonstrates high identification accuracy and low computational complexity for recognizing GSM, UMTS, and LTE cellular signals using real PSD measurements. Nevertheless, several opportunities exist to further enhance the system while preserving the original methodology. Future work may extend the framework to support 5G New Radio (NR) and emerging 6G communication technologies, enabling automatic identification across next-generation wireless networks. The incorporation of larger and more diverse measurement datasets collected under different propagation environments may further improve model robustness and generalization. In addition, adaptive hyperparameter optimization techniques and ensemble ELM models could be explored to enhance classification performance under challenging channel conditions. Integration of the proposed ELM framework with cognitive radio platforms and real-time spectrum monitoring systems may facilitate intelligent spectrum management and dynamic interference mitigation. Furthermore, hardware-oriented optimization for edge devices and software-defined radios can improve deployment efficiency while maintaining the fast learning capability that characterizes the proposed Extreme Learning Machine approach.

VI. EXPERIMENTAL RESULTS

The proposed Extreme Learning Machine (ELM) framework was experimentally evaluated to assess its effectiveness in identifying cellular communication signals using real Power Spectral Density (PSD) measurements. The evaluation focused on measuring classification accuracy, model robustness, computational efficiency, and generalization capability across two independent datasets, namely DS1 and DS2. The experimental analysis further compared the proposed ELM classifier with conventional neural network-based approaches to demonstrate its suitability for practical wireless communication systems.

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1. Performance on Dataset DS1

The DS1 dataset was employed during the model development stage to determine the optimal hyperparameter configuration for the Extreme Learning Machine. The dataset contains representative PSD measurements corresponding to GSM, UMTS, and LTE cellular communication systems. During experimentation, various ELM hyperparameters were evaluated to determine the configuration that provided the highest classification performance while maintaining low computational complexity.

The experimental results indicate that the proposed ELM classifier successfully learned discriminative spectral characteristics from the generated PSD images. As training progressed, the classifier demonstrated stable learning behavior and achieved high classification accuracy for all three communication technologies. The analytical computation of output-layer weights enabled rapid model convergence without requiring iterative gradient-based optimization, thereby substantially reducing training time while preserving reliable identification performance.

2. Generalization Performance on Dataset DS2

To evaluate model robustness, the optimized ELM classifier was tested using the independent DS2 dataset. Unlike DS1, this dataset was collected under different wireless measurement conditions and was not utilized during hyperparameter optimization. Consequently, DS2 provides an effective benchmark for assessing the generalization capability of the trained classifier.

The experimental evaluation demonstrates that the proposed ELM framework maintains consistent identification performance across both datasets without requiring additional parameter adjustment. The classifier accurately distinguishes among GSM, UMTS, and LTE signals despite variations in measurement conditions, confirming the ability of the proposed framework to generalize effectively to previously unseen PSD measurements. This robustness makes the proposed approach suitable for deployment in practical wireless monitoring environments where operating conditions frequently vary.

3. Classification Performance

The effectiveness of the proposed model was assessed using standard classification performance metrics. The obtained results indicate that the ELM classifier correctly identifies the majority of PSD measurements corresponding to the three cellular communication technologies. The generated confusion matrix further demonstrates strong discrimination capability, with only a limited number of misclassified samples observed among GSM, UMTS, and LTE categories.

The experimental findings confirm that transforming PSD measurements into two-dimensional binary images enables the classifier to capture representative spectral characteristics more effectively. This image-based representation improves the learning capability of the ELM while maintaining computational simplicity compared with conventional feature engineering techniques. Overall, the proposed methodology provides reliable signal identification suitable for intelligent radio applications.

4. Computational Performance Comparison

An important contribution of the proposed framework is its significantly lower computational complexity compared with conventional neural network architectures. The experimental comparison evaluates three computational aspects:

- Parameter Complexity
- Multiplication Complexity
- Addition Complexity

The analytical training mechanism employed by the Extreme Learning Machine substantially reduces the number of trainable parameters while eliminating iterative backpropagation. Consequently, the proposed classifier requires fewer multiplication and addition operations during training, resulting in considerably faster execution and lower computational resource consumption.

The comparison with existing deep learning approaches demonstrates that the ELM framework achieves competitive classification performance while requiring significantly less computational effort. This balance between classification accuracy and computational efficiency makes the proposed model highly suitable for real-time spectrum monitoring, cognitive radio systems, wireless network optimization, and software-defined radio platforms, where fast signal identification is essential.

Overall, the experimental analysis confirms that the proposed Extreme Learning Machine successfully identifies cellular communication signals using real PSD measurements while maintaining excellent computational efficiency and strong generalization capability. The combination of rapid learning, reduced complexity, and reliable classification performance establishes the proposed framework as an effective solution for intelligent wireless communication systems.

VII. DISCUSSION

The experimental evaluation demonstrates that the proposed Extreme Learning Machine (ELM) framework provides an efficient solution for automatic identification of cellular communication signals using real Power Spectral Density (PSD) measurements. By transforming one-dimensional PSD measurements into two-dimensional binary images, the proposed methodology enables the classifier to learn representative spectral characteristics without requiring manually designed feature extraction techniques. This automated learning capability contributes significantly to reliable identification of GSM, UMTS, and

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LTE communication signals under practical wireless operating conditions.

One of the major advantages of the proposed framework is its computational efficiency. Unlike conventional feedforward neural networks and deep learning models that require repeated parameter optimization through backpropagation, the Extreme Learning Machine analytically computes the output-layer weights after randomly initializing the hidden-layer parameters. This training strategy substantially decreases computational complexity while maintaining high classification performance. The complexity analysis confirms noticeable reductions in parameter complexity, multiplication operations, and addition operations, making the proposed framework highly suitable for real-time wireless communication systems.

The experimental validation performed using the independent DS1 and DS2 datasets further demonstrates the strong generalization capability of the proposed classifier. The model maintains consistent identification performance across different measurement environments without requiring additional retraining or parameter adjustment. Such robustness is particularly important for practical applications involving dynamic wireless environments, where communication signals are influenced by changing propagation conditions, interference, and spectrum utilization patterns.

Although the proposed framework achieves promising results, several practical challenges remain. Performance may be influenced by severe channel fading, low signal-to-noise ratios, spectrum congestion, and previously unseen wireless communication technologies. Furthermore, expanding the classifier to support emerging communication standards such as 5G and future 6G networks will require additional datasets and model validation under more diverse operating conditions.

Overall, the proposed Extreme Learning Machine successfully combines rapid learning, reduced computational complexity, and reliable classification accuracy into a unified automatic signal identification framework. These characteristics make the proposed system well suited for deployment in cognitive radio, dynamic spectrum access, electromagnetic surveillance, wireless spectrum monitoring, software-defined radio, and next-generation intelligent communication systems, where fast and accurate signal identification is a critical requirement.

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