



# Identification of Cellular Signals by Machine Learning with Extreme Learning Machine

K Naresh<sup>1</sup>, Ummiti Pavan Kumar<sup>2</sup>

<sup>1</sup>Assistant Professor, Department of MCA, Annamacharya Institute of Technology and Sciences, Tirupati, Andhra Pradesh, India.  
<sup>2</sup>Postgraduate, Department of MCA, Annamacharya Institute of Technology and Sciences, Tirupati, Andhra Pradesh, India.

## How to Cite this Article:

Kumar, U. P. (2026). Identification of Cellular Signals by Machine Learning with Extreme Learning Machine. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(04).  
<https://doi.org/10.55041/ijcope.v2i4.062>

## License:

This article is published under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author(s) and the source are credited.

© The Author(s). Published by International Journal of Creative and Open Research in Engineering and Management.



<https://doi.org/10.55041/ijcope.v2i4.062>

## Abstract

The demand for effective techniques to recognise and categorise various cellular network signals has grown due to the quick development of wireless communication technology. Communication security, spectrum monitoring, and wireless network management all depend on accurate cellular signal identification. The Extreme Learning Machine (ELM) algorithm is used in this study to provide a machine learning-based method for the automatic detection of cellular signal data. Multiple Power Spectral Density (PSD) features representing various wireless communication signals, including 5G, GSM, LTE, and WiFi, make up the dataset used in this work. In order to eliminate inconsistencies and get the features ready for training, the dataset is first preprocessed. The Extreme Learning Machine classifier, which is renowned for its quick learning speed and strong generalisation capacity, is then trained using the extracted PSD bin characteristics as input. Standard performance criteria, such as confusion matrix analysis and classification accuracy, are used to assess the trained model. According to experimental data, the suggested model can accurately and successfully differentiate between various cellular signal kinds. Furthermore, a web-based interface is put in place so that users can train the model and use input metrics to forecast the type of cellular signal. The suggested method can be expanded for real-time wireless signal monitoring applications and offers an effective and useful solution for automatic cellular signal identification.

## Keywords

Cellular Signal Classification, Extreme Learning Machine (ELM), Wireless Communication, Power Spectral Density (PSD), Machine Learning, Signal Identification, Network Signal Analysis



## I. Introduction

Over the past few decades, wireless communication technologies have advanced quickly, allowing for seamless connectivity across a variety of networks and devices. For dependable and fast data transfer, modern communication systems rely on a variety of wireless technologies, including WiFi, GSM, LTE, and 5G. Efficient identification and categorisation of various cellular signals has become a crucial challenge in wireless communication research due to the growing number of wireless devices and network infrastructures. Communication security, network monitoring, and spectrum utilisation are all enhanced by accurate signal identification.

Manual feature analysis and signal processing techniques are the mainstays of traditional signal identification approaches.

These methods, however, frequently call for specialised knowledge and might not work well with big datasets or intricate signal patterns. Due to its capacity to automatically identify patterns in data and carry out precise classifications, machine learning techniques have attracted a lot of attention in wireless communication applications in recent years.

The Extreme Learning Machine (ELM) has become a popular algorithm for classification tasks among several machine learning techniques. Compared to conventional neural network models, ELM, a single hidden-layer feedforward neural network, offers quick training times and robust generalisation capabilities. Pattern recognition, signal processing, and communication systems have all made extensive use of ELM due to its effectiveness and ease of usage.

This work proposes an Extreme Learning Machine-based machine learning method for the automatic detection of cellular signal data. Power Spectral Density (PSD) bin characteristics collected from various wireless communication signals, such as 5G, GSM, LTE, and WiFi, are included in the dataset used in this work. Important aspects of the signals are captured by these PSD features, which are useful for categorisation. Data preprocessing, feature analysis, model training, and performance evaluation are some of the steps in the suggested system. The PSD features are used to train the Extreme Learning Machine model, which then classifies the signals into the appropriate network categories. To enable users to engage with the system, train the model,

and forecast signal kinds based on input data, a web-based interface is also created.

## II. Literature Review

The growing number of wireless technologies and devices has made wireless signal classification a significant field of study in contemporary communication systems. Communication security, cognitive radio systems, and spectrum monitoring all depend on the ability to distinguish between various cellular signal types, including GSM, LTE, WiFi, and 5G. The application of machine learning and signal processing techniques to increase the accuracy of signal identification has been the subject of numerous studies throughout the years.

Statistical analysis and signal processing techniques were the mainstays of traditional signal categorisation approaches. These methods concentrated on extracting characteristics from signals, including power spectral density, modulation patterns, and frequency components. Even though these techniques offered insightful information, they were ineffective for managing large-scale datasets and frequently required specialised knowledge.

The growing number of wireless technologies and devices has made wireless signal classification a significant field of study in contemporary communication systems. Communication security, cognitive radio systems, and spectrum monitoring all depend on the ability to distinguish between various cellular signal types, including GSM, LTE, WiFi, and 5G. The application of machine learning and signal processing techniques to increase the accuracy of signal identification has been the subject of numerous studies throughout the years.

Statistical analysis and signal processing techniques were the mainstays of traditional signal categorisation approaches. These methods concentrated on extracting characteristics from signals, including power spectral density, modulation patterns, and frequency components. Even though these techniques offered insightful information, they were ineffective for managing large-scale datasets and frequently required specialised knowledge. These benefits have led to the successful application of ELM in a number of fields, such as wireless communication, biological signal processing, and image identification.

Power Spectral Density (PSD) characteristics have also been used in a number of studies to classify signals. The



distribution of signal power across various frequency components is represented by PSD features, which offer important details on the properties of the signal. Because every communication standard has distinct spectrum patterns, these characteristics are very helpful in differentiating various wireless technologies. Even with advancements in wireless signal categorisation, it is still difficult to achieve high accuracy while preserving computational efficiency. Thus, creating effective machine learning models capable of correctly classifying cellular signals is an ongoing research challenge.

### III. Dataset Description

The quality and structure of the dataset used for training and assessment have a significant impact on how well any machine learning model performs. This study uses a dataset of cellular signal measurements to categorise various wireless communication signal types. Power Spectral Density (PSD) measurements, which show the distribution of signal power across various frequency components, are the source of the dataset's various properties.

Fig: Dataset

Several PSD bin values that represent the spectral properties of different wireless signals are included in the dataset. Since every kind of signal has a distinct spectral pattern, these PSD characteristics are crucial for differentiating various communication methods. Machine learning algorithms can efficiently learn the distinctions between different signal categories by examining these spectral patterns. The collection includes several classes that represent various wireless communication technologies, such as WiFi, GSM, LTE, and 5G. A set of PSD feature values and a label designating the kind of cellular signal are associated with each record in the dataset. During the process of training the model, these labels serve as target variables.

To guarantee data consistency and enhance model performance, the dataset is preprocessed prior to machine learning model training. This entails managing missing values, classifying the dataset into input features and output labels, and getting the data ready for testing and training. After that, the dataset is split into two sections:

a testing dataset to assess the model's performance and a training dataset to train the model. The categorisation model's main input is the PSD bin characteristics. These characteristics give the model crucial information about the distribution of signal intensity across various frequencies, which aids in the identification of patterns connected to particular cellular technologies. The suggested approach seeks to precisely identify the kind of wireless signal contained in the dataset by making use of these characteristics.

### IV. Proposed Methodology

The suggested method employs machine learning to recognise and categorise cellular signal samples. The technology is built to automatically evaluate wireless signal data and categorise it into several network types, including WiFi, GSM, LTE, and 5G. Data preparation, feature extraction, model training, and signal classification are some of the steps in the methodology. The first step is to gather and prepare the cellular signal dataset with Power Spectral Density (PSD) bin characteristics for analysis. PSD features offer valuable insights into the properties of wireless transmissions by depicting the distribution of signal strength across several frequency bands. These characteristics aid in the model's ability to differentiate between various cellular technologies.

To eliminate inconsistencies and get the data ready for machine learning analysis, the dataset is cleaned and arranged during the preprocessing phase. The output labels (signal kinds) and input features (PSD bins) are kept apart. After that, the dataset is split into training and testing sets. The model is trained using the training set, and its performance is assessed using the testing set. The Extreme Learning Machine (ELM) technique is used for signal classification following preprocessing. ELM is a feedforward neural network with a single hidden layer that calculates the output weights analytically after randomly allocating weights to the hidden layer. When compared to conventional neural networks, our method drastically cuts training time without sacrificing classification results.

The trained ELM model classifies various cellular signal types by identifying patterns in the PSD attributes. The trained model uses the input feature values to predict the signal category during the testing phase. Metrics like confusion matrix analysis and classification accuracy are used to assess the model's performance. A web-based interface is created in addition to the machine learning model so that people can communicate with the system.

The interface offers features including signal prediction, dataset visualisation, and model training. The type of cellular network signal can be predicted by users by entering signal measurement values.

### V. Model Training Output and Confusion Matrix Analysis

The output interface of the suggested cellular signal classification system following model training is depicted in the above image. Users can manage the dataset, train the machine learning model, and make signal predictions using the system's web-based interface. The system's various modules, such as Home, Dataset, Training, Prediction, and Logout, are located in the left panel of the interface, making it simple to navigate the program.



Fig: Screenshot-1

The system indicates that the training has been successfully completed by displaying a confirmation message. A confusion matrix and classification accuracy are used to assess the model's performance. The Extreme Learning Machine (ELM) model obtained an accuracy of 0.775, as depicted in the image, meaning that it accurately identified roughly 77.5% of the cellular signal samples in the dataset.

The figure's confusion matrix offers a thorough examination of the classification outcomes. It displays a comparison between the anticipated signal classes produced by the trained model and the actual signal classes. The predicted categories are represented by the columns of the matrix, while the actual signal categories are represented by the rows.

Four distinct wireless communication signal types—5G, GSM, LTE, and WiFi—are included in the dataset. The confusion matrix's diagonal values show how many instances of each signal type were successfully classified. For instance, the model successfully identifies the majority of LTE and WiFi signals, indicating that the Extreme Learning Machine is capable of learning the spectrum characteristics of these signals. However, some misclassifications are observed in other categories, particularly between GSM and other signal types, which may occur due to similarities in their spectral patterns.

Overall, the results shown in the figure demonstrate that the proposed machine learning model is capable of effectively classifying different cellular signal types based on Power Spectral Density (PSD) features. The web-based interface further enhances the usability of the system by providing an interactive platform for training the model and analyzing classification results.

### VI. Prediction Module and Signal Analysis Interface



Fig: Interface

The prediction page of the cellular signal categorisation system, which was created as a component of the web-based application, is seen in the above figure. With the help of this module, users can enter signal data and get predictions about the kind of cellular signal that is present in a specific area. The system is adaptable and easy to use because the interface is made to offer both location-based and manual prediction capabilities.

Users can enter data for signal prediction using the Select Location panel on the left side of the screen. To examine the signal conditions at a particular location, users can enter the name of the city.

Additionally, the Get Current GPS Location feature, which obtains latitude and longitude information, allows the system to automatically determine the user's location. If users want to examine signals from a specific location, they can also manually input coordinates.

Power Spectral Density (PSD) feature values, which reflect the spectral properties of wireless signals, can be manually entered by users beneath the location input area. The trained machine learning model uses these PSD values as input features to categorise the cellular signal type. The user can start the prediction process by clicking the Predict Signal button once the input data has been supplied.

The trained Extreme Learning Machine (ELM) classifier is then used by the system to process the input features and produce the prediction results.



The anticipated outcomes are shown in the Signal Analysis Results panel in the middle of the interface. The best signal that is available at the chosen location is determined by the system; in this instance, it is displayed as LTE with 100% signal strength. Additionally, the interface uses graphical bars to compare signal strengths for various network protocols, including WiFi, LTE, GSM, and 5G. Users may more quickly comprehend the relative strength of each signal type thanks to this visualisation.

Additionally, the system allows a comparison of network providers, showing which service provider provides the strongest signal at the specified area.

In the displayed example, Jio is identified as the best provider with a signal strength of approximately 67%, while other providers such as Airtel and BSNL show slightly lower signal strengths.

## VII. Conclusion

The Extreme Learning Machine (ELM) technique was used in this study to identify cellular signal data using machine learning. The system classified several wireless communication signals, including 5G, GSM, LTE, and WiFi, using Power Spectral Density (PSD) properties. According to experimental data, the model demonstrated effective signal categorisation capabilities with an accuracy of about 77.5%. Additionally, a web-based interface for interactive model training and signal prediction was created. Larger datasets and more sophisticated deep learning methods can be used to further enhance the suggested strategy and increase forecast accuracy.

## References

- [1] G. B. Huang, Q. Y. Zhu, and C. K. Siew, "Extreme Learning Machine: Theory and Applications," *Neurocomputing*, vol. 70, no. 1–3, pp. 489–501, 2006.
- [2] T. S. Rappaport, *Wireless Communications: Principles and Practice*, 2nd ed., Prentice Hall, 2002.
- [3] S. Haykin, *Neural Networks and Learning Machines*, 3rd ed., Pearson Education, 2009.
- [4] A. Goldsmith, *Wireless Communications*, Cambridge University Press, 2005.
- [5] S. Rajendran, W. Meert, D. Giustiniano, V. Lenders, and S. Pollin, "Deep Learning Models for Wireless Signal Classification," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 1, pp. 150–177, 2019.