Machine Learning for EMSO Signal Classification

1. Introduction

Numerous applications central to radio frequency (RF) spectrum intelligence gathering rely on pattern recognition. For instance, classifying a signal by type requires identifying the specific modulation pattern associated with it. On the other hand, recognising the presence of an interesting signal within received data lead to distinguishing between the signal's pattern and background noise.

Traditionally, electromagnetic signals, like communication and radar signals, have been classified using handcrafted feature extractors tailored to specific signal types. Decision boundaries in low-dimensional feature spaces are then derived either analytically or statistically. However, achieving a rapid and autonomous understanding of the radio spectrum is vital for applications such as spectrum interference monitoring, radio fault detection, dynamic spectrum access, and various regulatory and defence purposes. Thus, automating these processes as much as possible is desirable for efficiency and error prevention due to fatigue. Machine learning (ML) methods, particularly those based on artificial intelligence, hold significant potential in enhancing the sensitivity and accuracy of Electromagnetic Spectrum Operation (EMSO) signal identification, especially in scenarios with short-time observations.

This paper provides some insights into various machine-learning approaches for EMSO signal classification and modulation recognition, focusing specifically on communication and radar signals supported by use cases within the electromagnetic spectrum domain.

2. Machine Learning for Automated Signal Classification

Automated signal classification involves automatically determining the signal characteristics of a series of gathered samples. This essential step follows signal detection and is significant in both civilian and military receiver systems. Leveraging ML, automated signal classification is a vital application that aims to identify the signal characteristics, such as modulation type and protocol, of an unidentified signal. For example, when confronted with a quadrature phase shift keying (QPSK) signal, the system should be able to recognise its utilisation of QPSK modulation accurately.

One of the popular traditional methods for automated signal classification is using decision trees. This approach involves extracting multiple numerical features from a captured signal, ranging from basic metrics like average power to more complex analyses like Fourier transformations. These features are then used sequentially in a predetermined order to create a branching 'tree' structure of decisions. However, decision trees operate in a linear fashion and can struggle with complex feature sets.

On the other hand, ML methods offer more flexibility and scalability for signal classification. ML algorithms also use extracted signal features to effectively differentiate between different signal types. An essential component of ML-based classification is the signal database, which should encompass signals from various conditions representative of the conditions under which the trained network is expected to function. Typically, this dataset is divided into a training set and a test set to optimise algorithm performance and prevent issues like overfitting and underfitting.

To evaluate the effectiveness of an ML algorithm, a confusion matrix is commonly used. This matrix displays how frequently signals of each type are identified as belonging to each possible category. A strong ML classifier will show most identifications along the diagonal of the matrix, indicating accurate performance. Confusion matrices not only reveal the classifier's reliability but also guide improvements by highlighting specific misclassifications that suggest areas for feature enhancement.

3. Automated Communication Signal Classification

Automated communication signal classification involves addressing an N-class decision problem, where the goal is to determine the modulation type of a received signal based on its complex base-band time series representation. A distinctive aspect of this approach is that the neural network's input consists of the raw In-phase (I) and Quadrature (Q) samples of each communication signal without undergoing expert feature extraction or preprocessing of the raw radio signal. Instead, the network learns directly from the high-dimensional raw time series data. Figure 1 illustrates an example neural network model designed for automated communication signal classification.

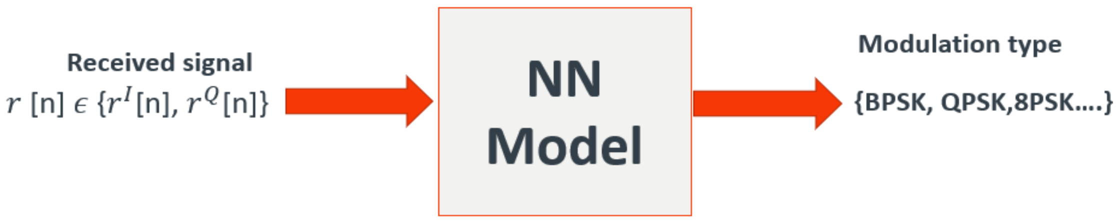

Figure 1- Example neural network model for automated communication signal classification.

3.1. Dataset

In our study, we used an open-source synthetic dataset that created using GNU Radio for the purpose of communication signal classification. This dataset comprises IQ samples representing 11 modulation classes (8 digital and 3 analogues) across 20 signal-to-noise ratio (SNR) values ranging from -20 dB to 18 dB. The structure of the dataset is depicted in Figure 2.

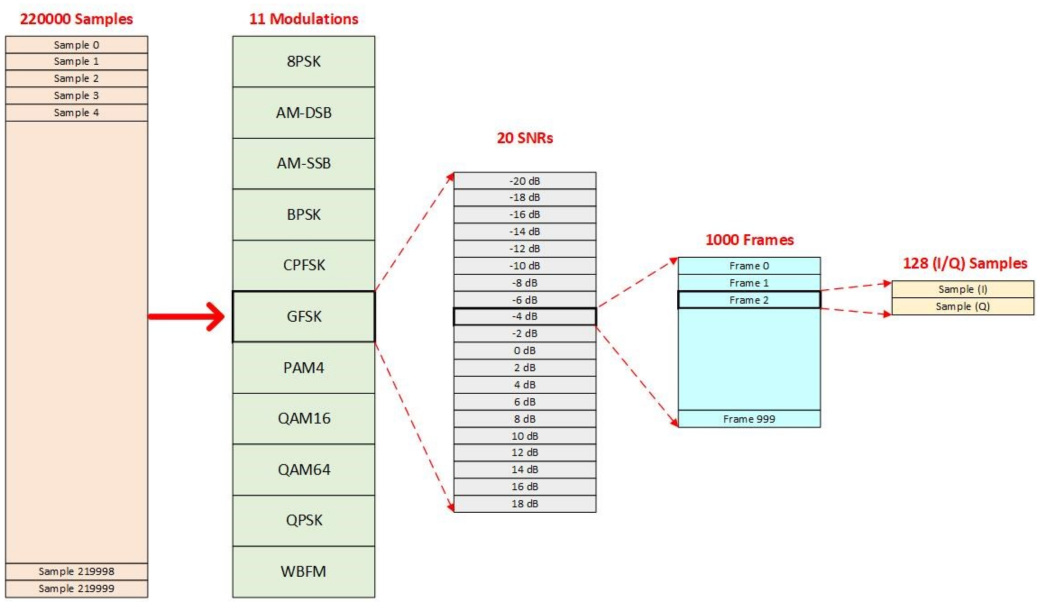

Figure 2 - The structure of the dataset used for communication signal classification.

3.2. Neural Network Models

When classifying communications signals, the most typical signal representation is time series, and the widely used method for its classification has been the one-dimensional Convolutional Neural Network (CNN). In our study, we considered two machine learning models for communication signal classification: CNN and Residual Network (ResNet). The ResNet model, known for its effectiveness in image recognition tasks with its ability to handle deep neural networks (150+ layers), has also shown promise in processing time-series data. Figures 3 and 4 illustrate the architecture of the CNN and ResNet models, respectively.

- CNN: This model consists of four layers, including two convolutional layers followed by two dense, fully connected layers. Each layer uses rectified linear (ReLU) activation functions, with a Softmax activation function applied to the output layer.
- ResNet: We implemented the residual network architecture, featuring convolutional layers, dense layers, and a skip connection. The skip connection, specifically between the input layer and the third convolutional layer, addresses the issue of gradient vanishing by facilitating a smoother flow of gradients during training. We particularly use ResNet50, a 50-layer convolutional neural network.

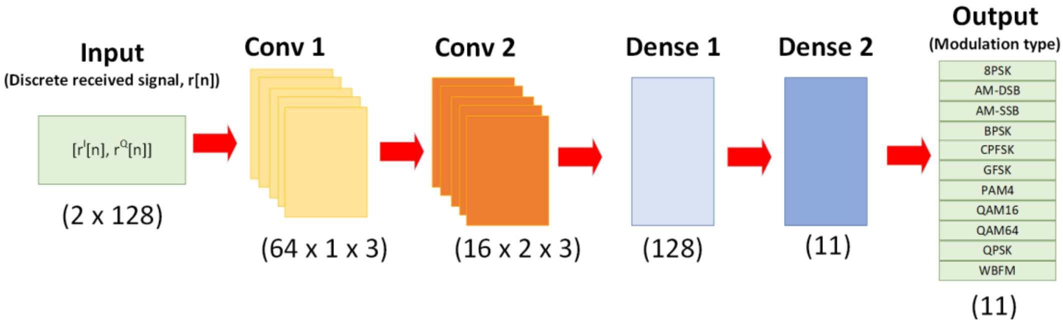

Figure 3 - CNN architecture.

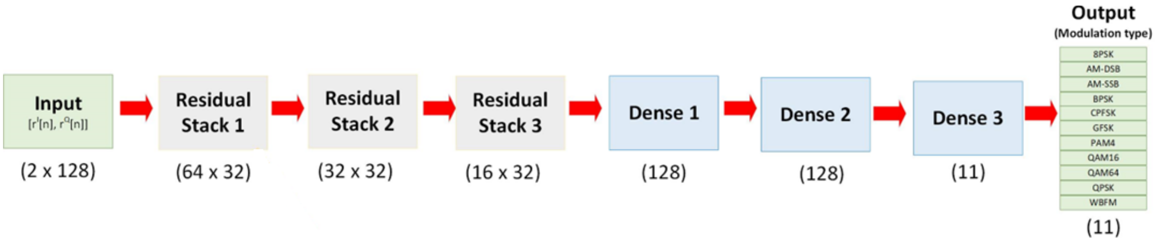

Figure 4 - ResNet architecture.

3.3. Performance Comparison of CNN and ResNet on Communication Signal Classification

To evaluate the performance of the CNN and ResNet models for communication signal classification, three main metrics are considered: variation of the loss function with the number of epochs, average accuracy across all classes based on SNR, and confusion matrices based on different SNRs. Loss function represents the penalty for incorrect predictions by the model. The objective during model training is to minimize this loss, aiming for accurate predictions across all examples.

Figure 5 demonstrates that the ResNet50 model achieves a significantly lower error rate compared to the CNN model. Specifically, ResNet50 achieves optimal performance after just 9 epochs, whereas the CNN model requires at least 50 epochs to reach similar performance levels.

In Figure 6, the impact of SNR ranging from -20 dB to 20 dB is illustrated, with confusion matrices for different SNR levels. Both models exhibit robustness and maintain high classification accuracy, particularly in high-SNR scenarios. Notably, the ResNet model demonstrates higher sensitivity and robustness compared to the CNN model, showcasing superior performance in signal classification tasks.

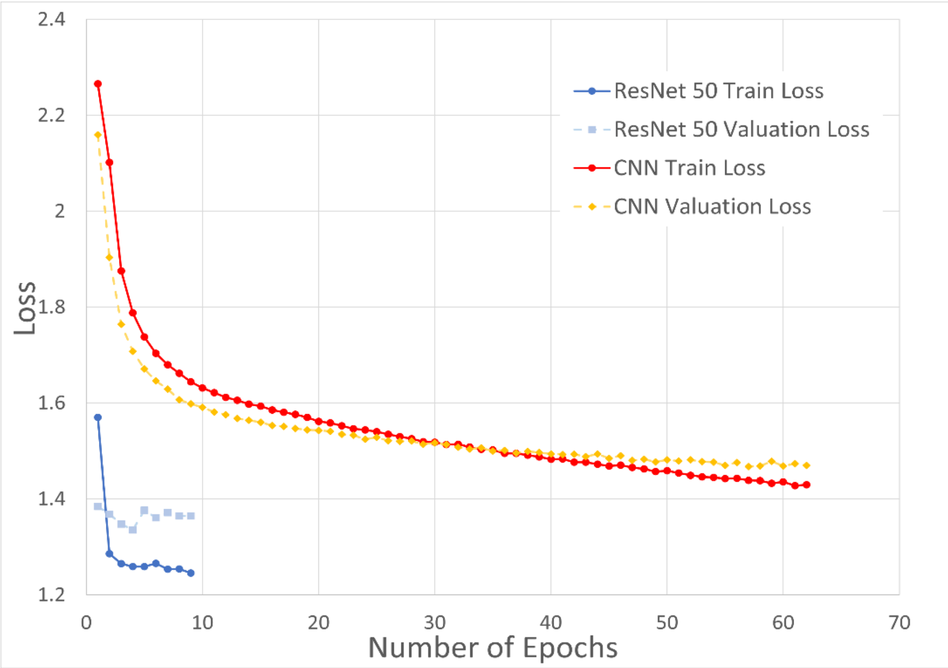

Figure 5 - Loss function with number of epochs for communication signal classification.

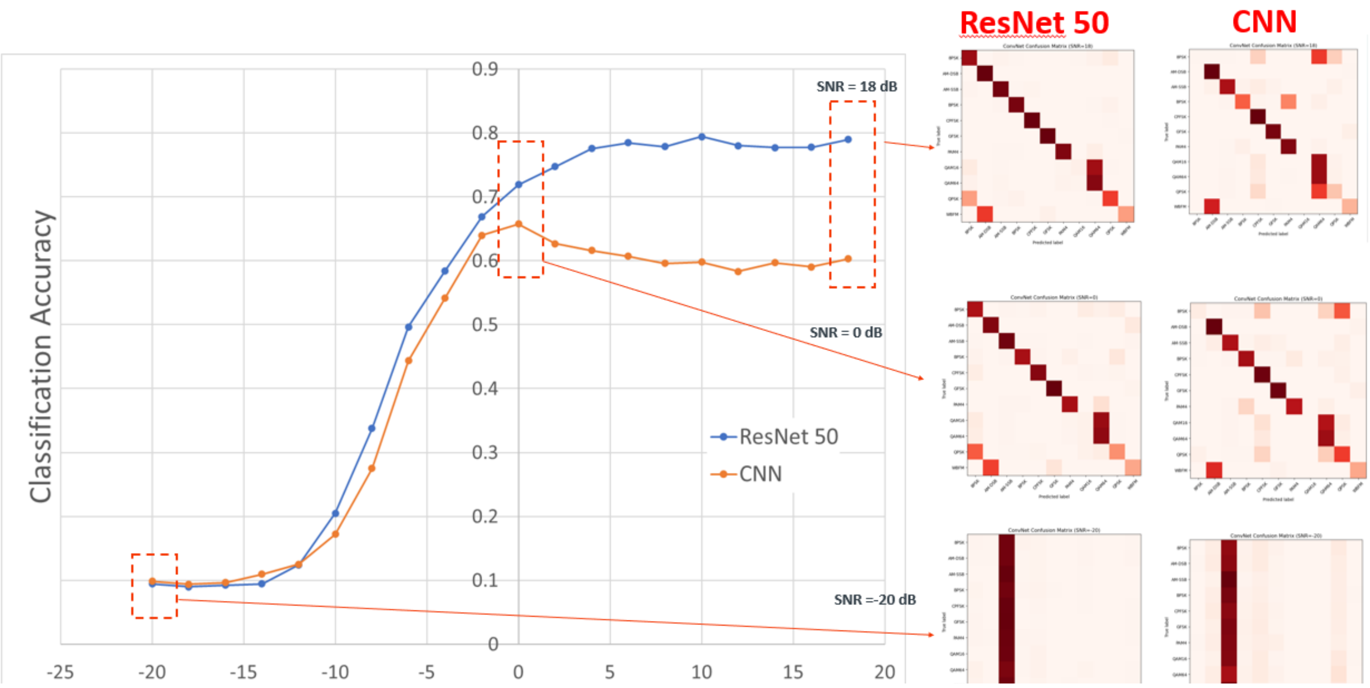

Figure 6 - Classification accuracy with SNR for communication signal classification.

4. Automated Radar Signal Classification

We considered a simple and unified scheme for classifying radar signals using Long-Short-Term Memory (LSTM) neural networks. The goal is to determine the modulation type of a received signal based on its complex base-band time series representation.

4.1. Dataset

In our study, we utilised an open-source dataset, which consists of time sequences of radar signal samples totalling 782,000 instances. These samples were generated through simulations on Matlab for the purpose of radar signal classification and to serve as a comprehensive radar dataset for future research endeavours. This dataset comprises IQ samples representing 23 modulation classes across 17 SNR values ranging from -12 dB to 20 dB. The structure of the dataset is depicted in Figure 7.

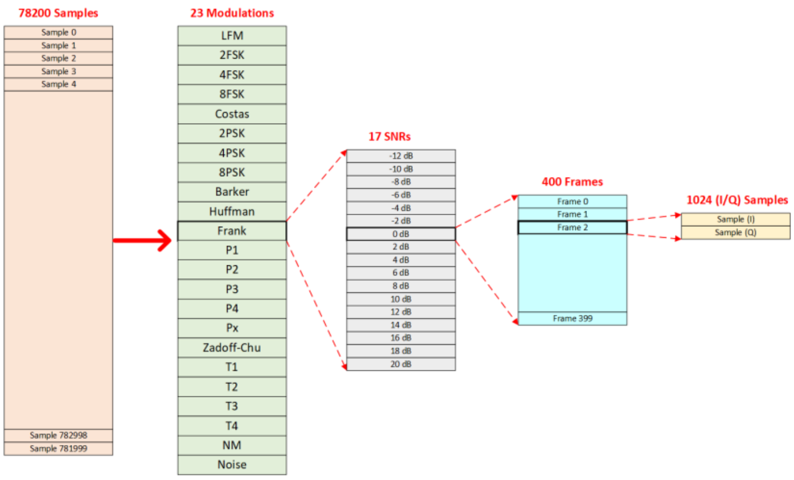

Figure 7 - The structure of the dataset used for radar signal classification.

4.2. LSTM Algorithm

LSTM networks are a type of deep learning architecture specifically designed for sequential data processing. Unlike traditional neural networks, LSTM networks are equipped with feedback connections that enable them to process entire sequences of data, rather than just individual data points. This capability makes LSTM networks highly effective in understanding and predicting patterns within sequential data types such as time series, text, and speech.

A typical LSTM network, depicted in Figure 8, comprises three fundamental components known as gates. These gates control the flow of information into and out of the LSTM memory cell, allowing for effective management of long-term dependencies within sequential data.

- **Forget gate:** chooses whether the information coming from the previous timestamp is to be remembered or is irrelevant and can be forgotten.
- **Input gate:** the cell tries to learn new information from the input to this cell.

- **Output gate:** the cell passes the updated information from the current timestamp to the next timestamp. This one cycle of LSTM is considered a single time set.

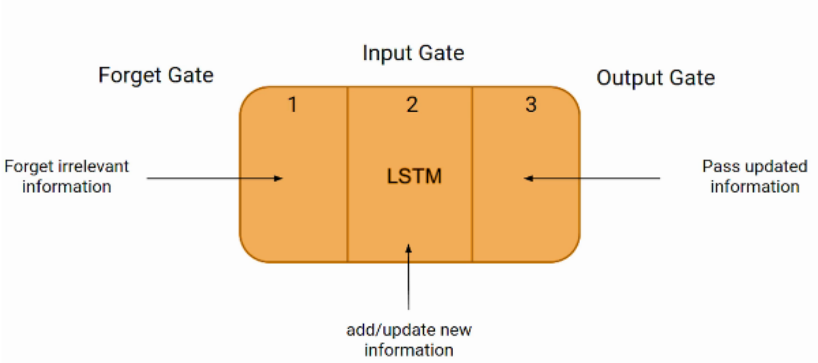

Figure 8 – Fundamental components of LSTM model.

Following the idea that LSTM networks are ideal for processing sequences, we considered a simple LSTM network shown in Figure 9 for Radar signal classification. This simplified network comprises three stacked LSTM layers, each containing 128 cells, followed by the output layer: the initial two LSTM layers return all sequence values (1024x128), while the final layer consolidates these sequences into a single value for each memory cell (1x128). Subsequently, the classification layer consists of a dense layer with a softmax activation function, featuring ***n*** output neurons corresponding to the classification classes.

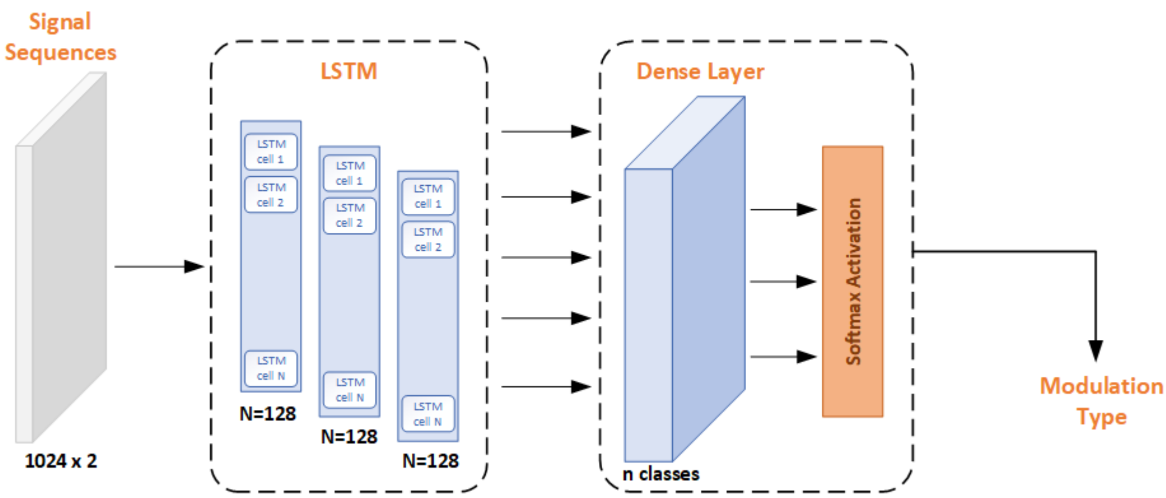

Figure 9 - LSTM architecture.

4.3. Performance of LSTM Algorithm on Radar Signal Classification

To evaluate the performance of the LSTM model for radar signal classification, two main metrics are used: Average accuracy across all classes based on SNR and the overall confusion matrix. Figure 10 illustrates the impact of SNR ranging from -12 dB to 20 dB. The LSTM network demonstrates robustness and maintains high classification accuracy, particularly in high-SNR scenarios. In Figure 11, the confusion matrix for overall performance for radar signal classification displays an achieved accuracy of 85%. However, it's noted that 4PSK and 8PSK signals are sometimes misclassified as each other due to similarities in their constellation diagrams. This limitation could potentially be addressed by initially classifying them as "PSK" and subsequently determining their specific order.

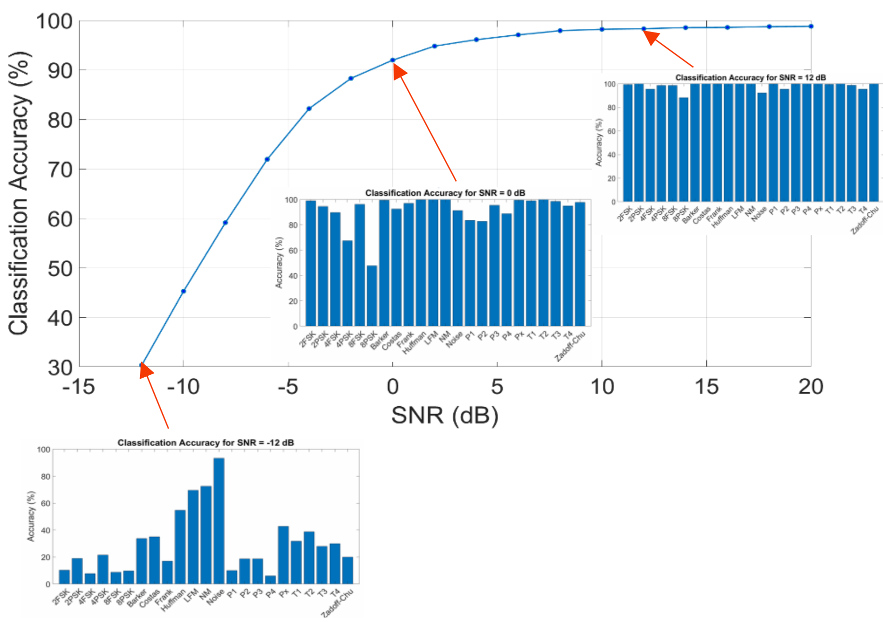

Figure 10 - Classification accuracy with SNR of LSTM model for Radar signal classification.

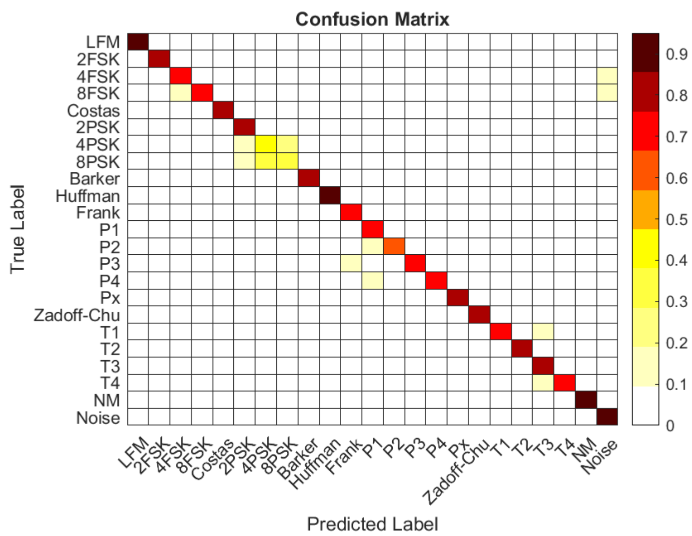

Figure 11 - Confusion matrix for overall performance of radar dataset with LSTM model.

5. Conclusion

We have successfully implemented machine learning techniques to automate critical processes in radio frequency (RF) spectrum intelligence gathering. Specifically, we have utilised a simple convolutional neural network (CNN) and a more sophisticated residual neural network (ResNet) to classify communication signals based on their modulation schemes. Additionally, we have demonstrated the application of the long-short-term memory (LSTM) algorithm for radar signal classification.

These applications represent significant progress towards achieving reliable and automated spectrum monitoring and analysis. However, there remains substantial potential for further enhancements as we continue to advance towards our goal of robust and automated spectrum monitoring and analysis systems. Ongoing research and development efforts will focus on refining these techniques to improve accuracy, efficiency, and adaptability in real-world scenarios.