Communication Engineering II Lab

EEE 4704

Project Title**: Modulation Classification using Deep Learning**

Submitted By**:**

- Rayan Hossain Khan, **190021214**
- Md. Sakib-Ul-Islam, **190021216**
- Shadman Saqib, **190021228**

Group: 04
Section: B2
Department: EEE

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Introduction

In the field of communication, modulation is the process of encoding information from a message signal into a carrier wave signal. The carrier wave is a high-frequency signal that is used to transmit the low-frequency message signal over long distances.

Modulation is used in a variety of communication systems, including radio, television, and cellular phone networks. It is an essential part of modern communication technology.

Here are some of the benefits of modulation:

- Efficient use of bandwidth: Modulation allows multiple signals to be transmitted over a single channel. This makes it possible to use the available bandwidth more efficiently.
- Reduced noise interference: Modulation can help to reduce the effects of noise on the transmitted signal. This is because the noise is less likely to affect the high-frequency carrier wave than the low-frequency message signal.
- Increased transmission range: Modulation allows signals to be transmitted over longer distances. This is because the high-frequency carrier wave is less likely to be attenuated by obstacles than the low-frequency message signal.
- Smaller antenna size: The size of an antenna is determined by the wavelength of the signal it is transmitting. The wavelength is inversely proportional to the frequency of the signal, so the higher the frequency, the shorter the wavelength.

Modulation classification is the process of identifying the modulation type of a received radio signal. It is an important task in wireless communication for several reasons:

- Spectrum management: Modulation classification can be used to identify the type of signal that is occupying a particular frequency band. This can then be used to allocate the band to the most appropriate user.

- <u>Adaptive modulation</u>: It can be used to adapt the modulation type of a transmitter to the current channel conditions. This can improve the performance of the communication system by reducing the effects of noise and interference.
- <u>Spectrum sensing</u>: It can be used to identify the presence of unauthorized users in a spectrum band. This can then be used to take action to block or interfere with the unauthorized signal.
- <u>Signal classification</u>: It can be used to classify the type of signal that is being received. This can then be used to determine the source of the signal and the type of information that it is carrying.

There are a number of different approaches to modulation classification. Some of the most common approaches include:

- <u>Likelihood-based methods</u>: These methods use statistical models to estimate the likelihood that a signal is of a particular modulation type.
- <u>Feature-based methods</u>: They extract features from the received signal and use these features to classify the modulation type.
- <u>Machine learning methods</u>: They use machine learning algorithms to classify the modulation type. We will be using one of these methods in our project.

Deep learning has emerged as a powerful tool for modulation classification due to its ability to extract complex patterns from such data. Here are some of the key reasons for using deep learning in modulation classification:

- <u>Automatic feature extraction</u>: Deep learning algorithms can automatically learn relevant features from the raw signal data, eliminating the need for manual feature engineering. This is particularly beneficial in modulation classification, where the underlying signal characteristics can be subtle and difficult to capture manually.
- <u>Robustness to noise and interference</u>: They can be trained to be robust to noise and interference, which are common challenges in wireless communication environments. This robustness is achieved by learning to focus on the relevant signal features while suppressing noise and interference.
- <u>High classification accuracy</u>: They have demonstrated the ability to achieve high classification accuracy in modulation classification tasks. This is due

to their ability to learn complex relationships between the signal features and the modulation type.

- Adaptability to new modulation schemes: They can be adapted to new modulation schemes by retraining them on data from the new schemes. This adaptability is crucial in the ever-evolving world of wireless communication, where new modulation schemes are constantly being developed.
- End-to-end learning: They can be trained in an end-to-end manner, directly from the raw signal data to the modulation classification output. This eliminates the need for intermediate preprocessing steps, which can introduce errors and reduce accuracy.

Literature Review

Traditional techniques for modulation classification have been widely used for many years, but they have limitations that can affect their performance in complex and noisy environments. Here's a discussion of traditional techniques and their limitations:

1. Likelihood-Based Methods: Likelihood-based methods, such as maximum likelihood estimation (MLE) and Bayesian classifiers, rely on statistical models to determine the likelihood that a received signal corresponds to a particular modulation scheme. They are well-suited for low-signal-to-noise ratio (SNR) scenarios and are robust to noise and interference. But the limitations are:
    a. Reliant on accurate statistical models, which may not always be available or accurate for complex modulation schemes
    b. Computationally expensive, especially for high-dimensional signal representations
2. Feature-Based Methods: Feature-based methods extract specific characteristics from the received signal, such as signal amplitude, frequency, or phase variations, and use these features as inputs for a classifier. Common classifiers include support vector machines (SVMs) and decision trees. Their limitations are:
    a. Feature extraction can be challenging for complex signals, and the choice of features can significantly impact classification performance
    b. Limited ability to handle non-stationary signals and noise interference
3. Machine Learning Methods: Machine learning methods, such as SVMs and neural networks, can learn complex relationships between features and modulation types from training data. They are adaptable to new modulation schemes and can handle noisy environments. Their limitations are:
    a. Require large amounts of training data, which may not always be available
    b. Interpretability of results can be limited, making it difficult to understand which features contribute most to the classification decision
4. Deep Learning Methods: Deep learning methods, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have emerged as powerful tools for modulation classification, demonstrating

superior performance compared to traditional methods. They can automatically extract features from raw signal data and handle complex modulation schemes with high accuracy. Their limitations are:

a. Computational complexity and data requirements, which may be challenging for real-time applications
b. Limited interpretability of results, making it difficult to understand the decision-making process of the deep learning model

Deep learning has emerged as a powerful tool for modulation classification, demonstrating superior performance compared to traditional methods. Recent studies have focused on enhancing the effectiveness and applicability of deep learning in this domain. Here's a review of recent advancements in using deep learning for modulation classification:

- <u>Convolutional Neural Networks (CNNs)</u>
  CNNs have been extensively employed for modulation classification due to their ability to extract spatial features from signal representations. Studies have explored various CNN architectures, such as VGGNet, ResNet, and DenseNet, for modulation classification tasks.
  <u>Reference</u>: Wang, W., et al. (2017). Deep neural network based automatic modulation classification. IEEE Communications Letters, 21(2), 373-376.
- <u>Recurrent Neural Networks (RNNs):</u>
  RNNs are well-suited for modeling temporal dependencies in modulation signals, making them suitable for classifying time-varying modulation schemes. Studies have investigated various RNN architectures, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), for modulation classification.
  <u>Reference</u>: O'Shea, T., et al. (2016). Convolutional neural networks for automatic modulation classification. IEEE Transactions on Signal Processing, 64(11), 3224-3236.
- <u>Attention Mechanisms</u>:
  Attention mechanisms have been incorporated into deep learning models to focus on relevant regions of the signal, enhancing feature extraction and classification performance. Studies have explored various attention mechanisms, such as self-attention and multi-head attention, for modulation classification.
  <u>Reference</u>: Li, S., et al. (2018). Modulation classification with convolutional

neural networks and attention mechanisms. IEEE Communications Letters, 23(5), 645-648.

- Data Augmentation Techniques:
  Data augmentation techniques have been employed to expand the training dataset and improve the generalization ability of deep learning models. Studies have investigated various data augmentation techniques, such as time-frequency warping, noise addition, and channel fading, for modulation classification.
  Reference: Wang, X., et al. (2020). Data augmentation for deep learning-based automatic modulation classification. IEEE Transactions on Vehicular Technology, 69(11), 13832-13843.
- Transfer Learning:
  Transfer learning has been utilized to leverage pre-trained deep learning models for modulation classification, reducing training time and improving performance. Studies have explored various transfer learning approaches, such as fine-tuning and feature extraction, for modulation classification.
  Reference: Jiang, Y., et al. (2020). Transfer learning for automatic modulation classification with deep neural networks. IEEE Access, 8, 224978-225021.

Methodology

The trained CNN in our project can recognize these eight digital and three analog modulation types:

- Binary phase shift keying (BPSK)
- Quadrature phase shift keying (QPSK)
- 8-ary phase shift keying (8-PSK)
- 16-ary quadrature amplitude modulation (16-QAM)
- 64-ary quadrature amplitude modulation (64-QAM)
- 4-ary pulse amplitude modulation (PAM4)
- Gaussian frequency shift keying (GFSK)
- Continuous phase frequency shift keying (CPFSK)

- Broadcast FM (B-FM)
- Double sideband amplitude modulation (DSB-AM)
- Single sideband amplitude modulation (SSB-AM)

The main 4 sections of our project is discussed below:

1. **Waveform Generation**
   We generate 10,000 frames for each modulation type, where 80% is used for training, 10% is used for validation and 10% is used for testing. We use training and validation frames during the network training phase. Final classification accuracy is obtained using test frames.
   Each frame is 1024 samples long and has a sample rate of 200 kHz. For digital modulation types, eight samples represent a symbol. The network makes each decision based on single frames rather than on multiple consecutive frames. We assumed a center frequency of 902 MHz and 100 MHz for the digital and analog modulation types, respectively.
   We can either choose to train a network or load a pre-trained network for saving some time and resources.
   Each of the frame passes through a channel with the following:
   a. **AWGN**: The channel adds AWGN with an SNR of 30 dB. It is implemented using the "*awgn"* function.
   b. **Rician Multipath**: The channel passes the signals through a Rician multipath fading channel using the *"comm.RicianChannel"* System object. We assumed a delay profile of [0 1.8 3.4] samples with

corresponding average path gains of [0 -2 -10] dB. The K-factor is 4 and the maximum Doppler shift is 4 Hz, which is equivalent to a walking speed at 902 MHz.

c. **Clock Offset**: Clock offset occurs because of the inaccuracies of internal clock sources of transmitters and receivers. Clock offset causes the center frequency, which is used to downconvert the signal to baseband, and the digital-to-analog converter sampling rate to differ from the ideal values.

Using the *"helperModClassTestChannel"* object, we can apply all three channel impairments to the frames.

We create a loop that generates **channel-impaired frames** for each modulation type and stores the frames with their corresponding labels in MAT files. By **saving** the data into files, we can prevent the need to generate the data every time we run this code. We can also share the data more effectively.

Removing a random number of samples from the beginning of each frame, we can remove transients and make sure that the frames have a random starting point with respect to the symbol boundaries.

Then we **plot** the real and imaginary parts of the example frames and also their spectrogram.

We use a *"signalDatastore"* object to manage the files that contain the generated complex waveforms. **Datastores** are especially useful when each individual file fits in memory, but the entire collection does not necessarily fit.

Neural network training is **iterative**. At every iteration, the datastore reads data from files and transforms the data before updating the network coefficients. If the data fits into the memory of our computer, importing the data from the files into the memory enables faster training by eliminating this repeated read from file and transform process. Instead, the data is read from the files and transformed once. Training this network using data files on disk takes about a lot more time than training using in-memory data.

2. **Train the CNN**
   We **divide** the frames into training, validation, and test data using the *“helperModClassSplitData”* function.

   Then we train a CNN that consists of **six convolution layers** and **one fully connected layer**. Each convolution layer except the last is followed by a **batch normalization** layer, rectified linear unit (**ReLU**) activation layer, and **max pooling** layer. In the last convolution layer, the max pooling layer is replaced with an **average pooling** layer.

   The **mini-batch size** is set as 256 and the maximum number of **epochs** as 12, since a larger number of epochs provides no further training advantage. The initial **learning rate** is set to $2 \cdot 10^{-2}$ and it is reduced by a factor of 10 every 9 epochs. On an Nvidia 1660ti GPU, the network takes approximately 10 minutes to train.

   We evaluate the trained network by obtaining the **classification accuracy** for the test frames and plot the **confusion matrix**.

3. **Predict Modulation Type Using CNN**
   The trained CNN can take 1024 channel-impaired samples and predicts the modulation type of each frame. We generate several PAM4 frames that are impaired with Rician multipath fading, center frequency and sampling time drift, and AWGN.

   We observe the classifier predictions, which are analogous to hard decisions. The network correctly identifies the frames as PAM4 frames. This is easily done by the *“helperModClassGetModulator”* function.

4. **Test with SDR**
   To test the performance of the trained network with over-the-air signals, we can use the *“helperModClassSDRTest”* function. To perform this test, we must have dedicated SDRs for transmission and reception. We can use two **ADALM-PLUTO** radios, or one ADALM-PLUTO radio for transmission and one USRP® radio for reception. We must install the Communications Toolbox Support Package for ADALM-PLUTO Radio. The *“helperModClassSDRTest”* function uses the same modulation functions as

used for generating the training signals, and then transmits them using an ADALM-PLUTO radio. Instead of simulating the channel, we capture the channel-impaired signals using the SDR that is configured for signal reception (ADALM-PLUTO radio). We use the trained network with the same classify function used previously to predict the modulation type.

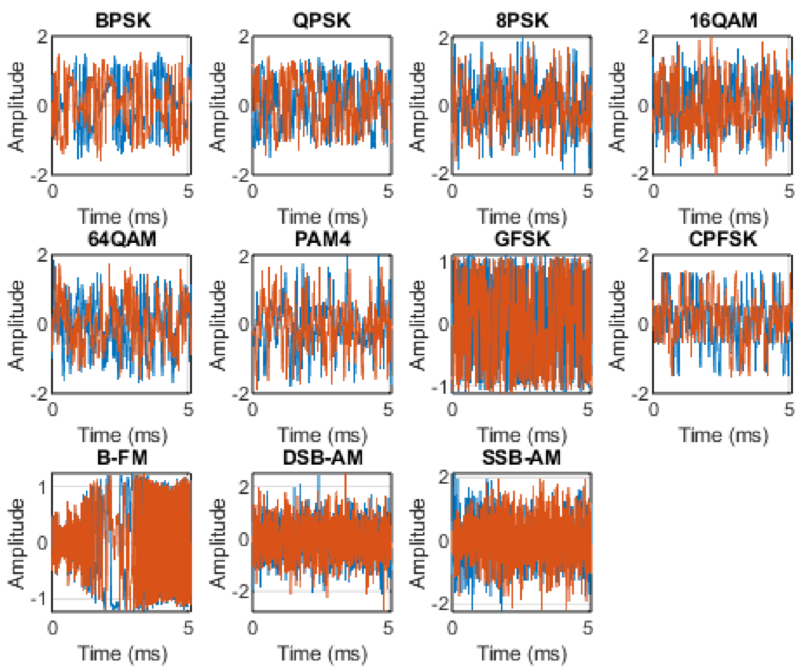
Here are some of the important MATLAB functions and objects used:

- **randi**: Generates random bits
- **pammod**: PAM4-modulates the bits
- **rcosdesign**: Designs a square-root raised cosine pulse shaping filter
- **filter**: Pulse shapes the symbols
- **comm.RicianChannel**: Applies Rician multipath channel
- **comm.PhaseFrequencyOffset**: Applies phase and/or frequency shift due to clock offset
- **interp1**: Applies timing drift due to clock offset
- **awgn**: Adds AWGN

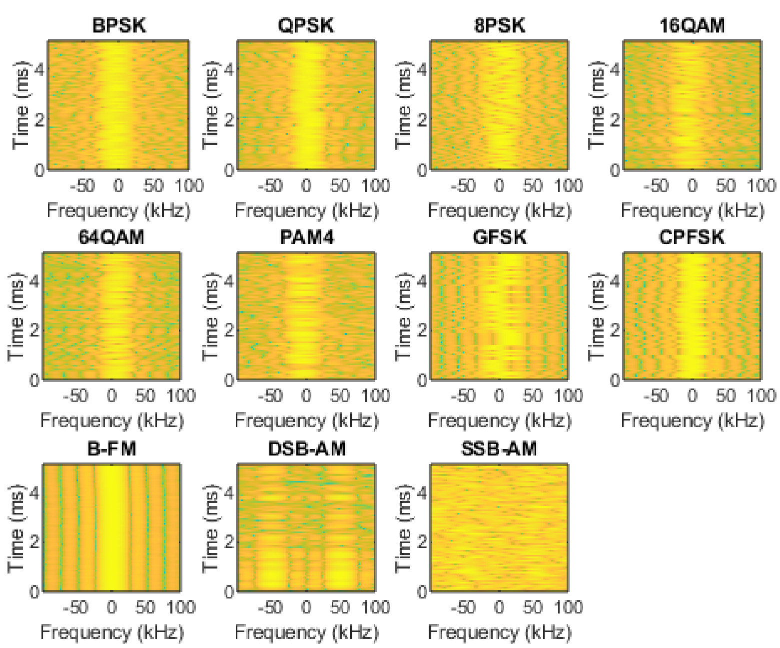
- **helperModClassGetModulator.m**: It is used for generating modulated signals
- **helperModClassTestChannel.m**: It is used to simulate and test communication channel impairments
- **helperModClassGetSource.m**: It is used to generate symbol sequences for modulation classification tasks
- **helperModClassFrameGenerator.m:** It is used to generate frames of modulated signals
- **helperModClassCNN.m**: It is used to design and train convolutional neural networks (CNNs)
- **helperModClassTrainingOptions.m**: It is used to configure training options for convolutional neural networks (CNNs)

Results

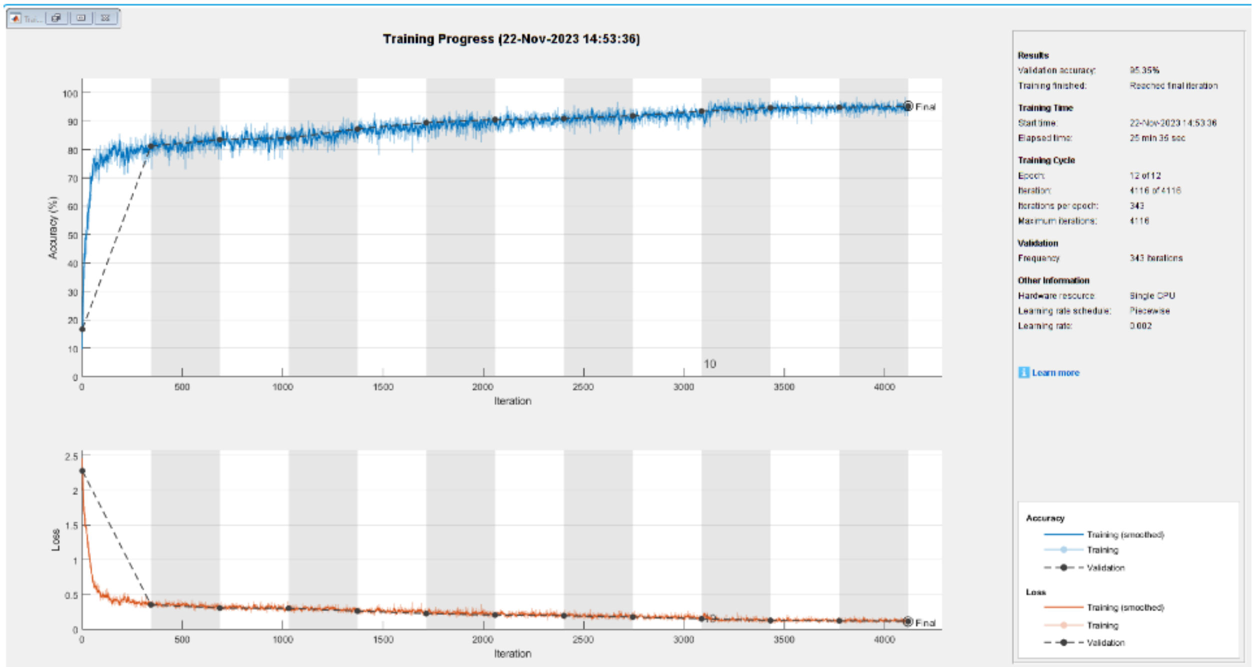
Plot of the amplitude of the real and imaginary parts of the example frames against the sample number:



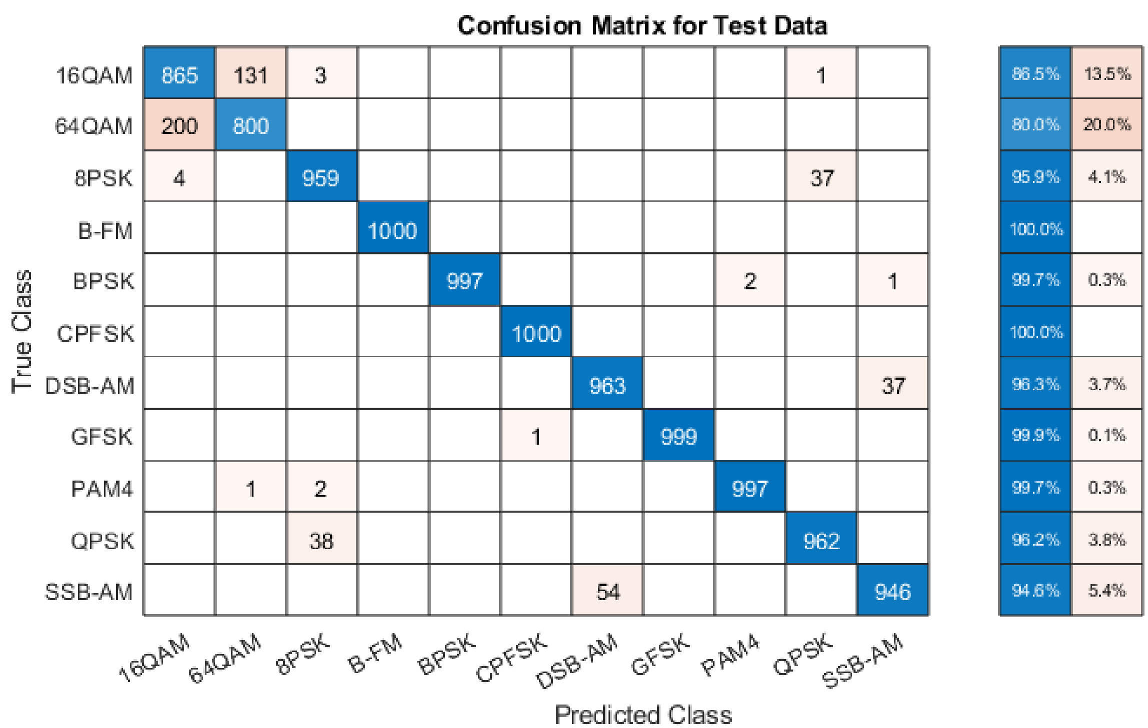
Plot of the spectrogram of the example frames:



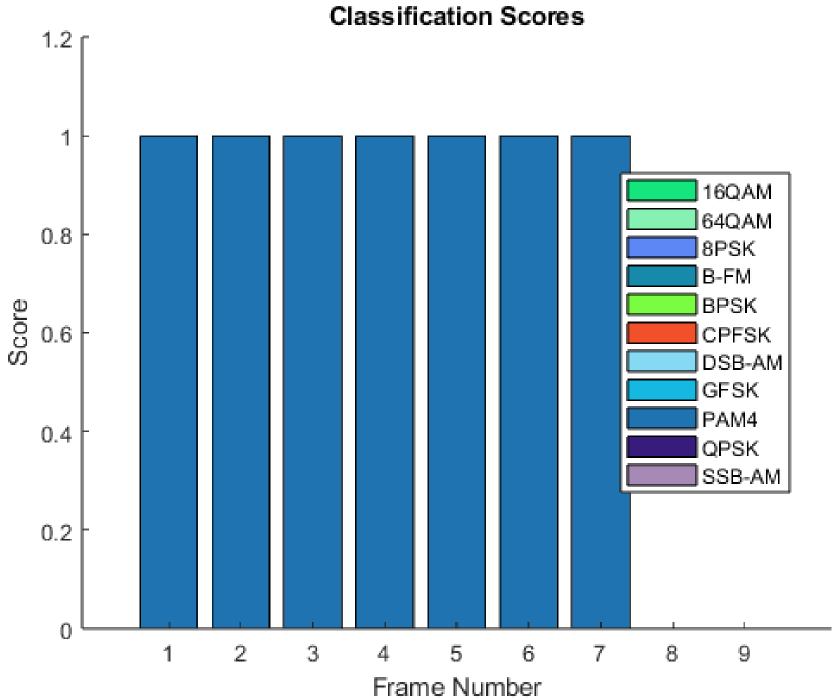
Plot of the training progress shows, the network converges in about 12 epochs to more than 95% accuracy.



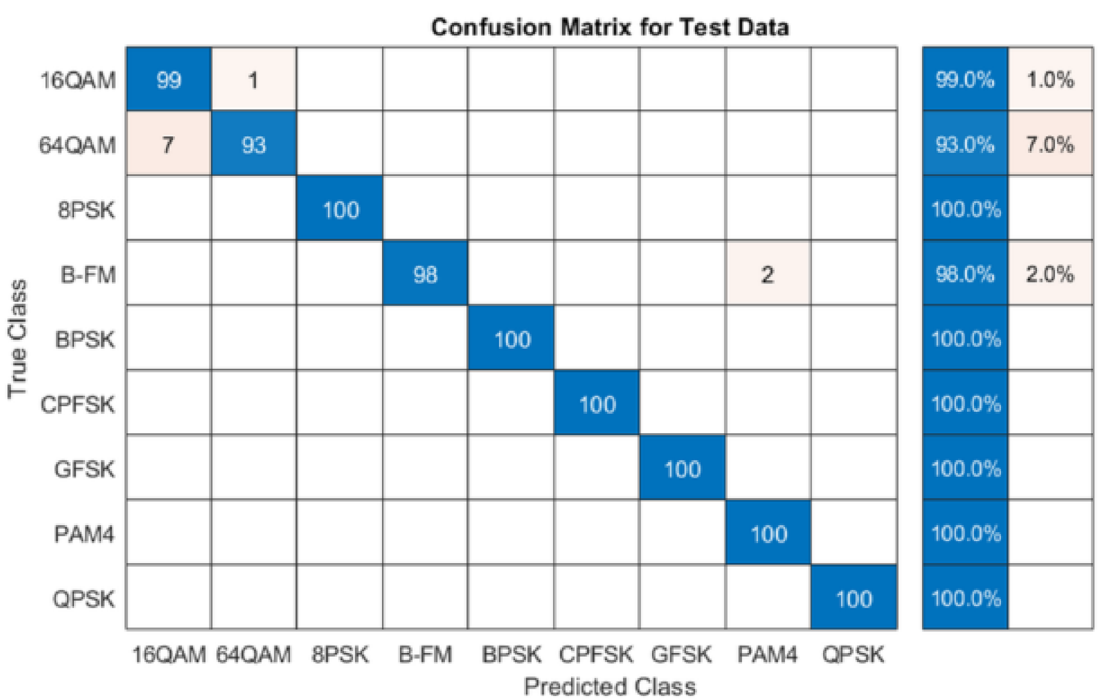
Plot of the confusion matrix for the test frames. As the matrix shows, the network confuses 16-QAM and 64-QAM frames. This problem is expected since each frame carries only 128 symbols and 16-QAM is a subset of 64-QAM.



Classifier predictions of the trained CNN where the network correctly identifies the frames as PAM4 frames:



When using two stationary ADALM-PLUTO radios separated by about 2 feet, the network achieves 99% overall accuracy with the following confusion matrix.



Conclusion

A brief summary of the key findings of our project "Modulation Classification using Deep Learning" is given below:

- Deep learning has emerged as a powerful tool for modulation classification, outperforming traditional methods in terms of accuracy, robustness, and adaptability.
- Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are particularly well-suited for modulation classification, due to their ability to extract features from complex signal representations.
- Attention mechanisms can further enhance the performance of deep learning models for modulation classification by focusing on relevant regions of the signal.
- Data augmentation techniques can be employed to expand the training dataset and improve the generalization ability of deep learning models.
- Transfer learning can be utilized to leverage pre-trained deep learning models for modulation classification, reducing training time and improving performance.
- Despite its advancements, deep learning still faces challenges in terms of computational complexity and interpretability.

The main workflow of the project is:

- Generating waveforms
- Training with CNN
- Testing the CNN
- Testing with SDR

Future Work

Deep learning has revolutionized modulation classification, achieving remarkable performance in identifying and classifying various modulation schemes employed in communication systems. However, despite its significant advancements, there remains room for further improvement and exploration in this domain. Here are some potential areas for future research or improvements to deep learning in modulation classification:

- Enhancing Robustness to Noise and Interference
- Handling Non-Stationary Signals
- Reducing Computational Complexity
- Improving Interpretability
- Exploring Transfer Learning and Meta-Learning
- Investigating Novel Deep Learning Architectures
- Addressing the Challenges of Imbalanced Data
- Developing Multi-Task Learning Approaches
- Investigating Explainable AI (XAI) Techniques
- Exploring Federated Learning for Privacy-Preserving Classification

By addressing these potential areas for future research and improvements, deep learning can continue to revolutionize modulation classification, enabling more reliable, efficient, and interpretable classification of modulation schemes in modern communication systems.

References

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2. O'Shea, T. J., T. Roy, and T. C. Clancy. "Over-the-Air Deep Learning Based Radio Signal Classification." IEEE Journal of Selected Topics in Signal Processing. Vol. 12, Number 1, 2018, pp. 168–179.
3. Liu, X., D. Yang, and A. E. Gamal. "Deep Neural Network Architectures for Modulation Classification." Preprint, submitted January 5, 2018. https://arxiv.org/abs/1712.00443v3

Individual contribution of team members

ID	Works done	Overall Contribution
190021214	Project Idea, Coding, overall Structure	40%
190021216	Project report, Presentation, Commenting	30%
190021228	Hyperparameter Tuning, Training and testing with GPU	30%