ENSEMBLE LEARNING APPROACH FOR DIGITAL COMMUNICATION MODULATION'S CLASSIFICATION

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ABSTRACT

This work uses artificial intelligence to create an automatic solution for the modulation's classification of various radio signals. This project is a component of a lengthy communications intelligence process that aims to find an automated method for demodulating, decoding, and deciphering communication signals. As a result, the work we did involved selecting the database required for supervised deep learning, assessing the performance of current methods on unprocessed communication signals, and suggesting a deep learning network-based method that would enable the classification of modulation types with the best possible ratio between computation time and accuracy. In order to use the current automatic classification models as a guide, we first conducted study on them. As a result, we suggested an ensemble learning strategy based on Transformer Neural Network and adjusted ResNet that takes into account the difficulty of forecasting in low Signal Noise Ratio (SNR) scenarios while also being effective at extracting multi-scale characteristics from the raw I/Q sequence data. Ultimately, we produced an architecture for communication signals that is simple to work with and implement. With an accuracy of up to 95%, this solution's optimum and sturdy architecture decides the type of modulation on its own.

KEYWORDS

Automatic modulation classification, Artificial Intelligence, Deep Learning & Modulationn recognition.

1. INTRODUCTION

Intelligence systems entrusted with keeping an eye on the communications spectrum have a tough problem when it comes to communication signals, which are characterized by a variety of modulations to achieve high data rates while limiting interference. When modulations get more complex, so do the identification and demodulation processes. This is especially true when trying to extract useful information in the field of Communications Intelligence (COMINT).

Within the COMINT area, the study concentrates on the complex problem of identifying and categorizing modulations in intercepted signals, where the main goal is to extract relevant information. This is essential for figuring out the kind of transmission and making the demodulation procedure easier. Decoding communication signals, whether voice or data, is the focus of Communications Intelligence (COMINT), as opposed to Electronic Intelligence (ELINT), which mostly works with radars.

Modulation is a basic mechanism in the communication signals used to transmit information. By modulating the data into a certain frequency, air attenuation issues are resolved and high-speed transmission is made possible. The Intelligence process begins with the interception of an unknown signal in the wide communications spectrum. Frequency and signal strength measurements are involved. But figuring out the modulation to employ while sending the radio signal is the first and most important step. In the past, intelligence methods required repeatedly using different demodulators. However, this strategy has been shown to be slow and unproductive, especially when dealing with contemporary modulations. The development of Artificial Intelligence (AI) has drastically changed this environment. The wireless research community has paid close attention to the automatic classification of modulation types at the receiver, which has the notable benefit of increasing spectrum use efficiency. Early attempts used Convolutional Neural Network (CNN) architectures and applied spectrogram images produced by various modulations.

The Inphase and Quadrature signals (I/Q) of a signal also known as the "DNA" of any signal have been used in recent studies in a novel way. In automatic modulation recognition, I/Q data has proven to perform better than conventional methods. Any signal consists of two parts, essentially: the quadrature (Sinus) and the in-phase (Cosine) components. The complex baseband signal described by these I/Q samples has waveforms denoting its real and imaginary components, I(t) and Q(t).

The substance of the signal is captured in the whole signal description, $X(t) = I(t)+jQ(t)$, which is encoded into a matrix with two rows for I and Q. This I/Q-based methodology for modulation categorization turns out to be a potent tool, offering a thorough and efficient way to interpret the complex modulations seen in contemporary communication signals.

2. Background

Automatic Modulation Classification (AMC) techniques encompass a spectrum of methodologies, broadly categorized into traditional approaches, where most of them are basically categorized into the likelihood-based (LB) and feature-based (FB) approaches and advanced techniques leveraging deep learning.

2.1. Traditional Approaches

2.1.1. Likelihood-Based Methods

In the early days of Automatic Modulation Classification (AMC), most approaches were likelihood-based. These techniques entail precisely determining likelihood functions for various modulation kinds. The basic idea is to find the most likely modulation type by comparing the received signal to a set of specified likelihood functions. In situations where there is both known and unknown channel information, modulation identification problems are addressed using likelihood-based techniques, which make use of theoretical models and probability theories [1]. These methods need significant computing complexity for model parameter estimation, even if they can reach ideal classification accuracy provided complete knowledge of the signal and channel models is assumed [2], [3].

2.1.2. Feature-Based Approaches

Feature-based methods are a basic method for differentiating modulation patterns in the context of AMC. This approach, which strikes a practical compromise between classification accuracy and computing efficiency, is based on feature extraction and classifier construction. The basic idea is to capture the unique properties of different signals without having to deduce the signal's likelihood function in great detail. Two crucial steps in the feature-based method are pre-processing the signal and extracting pertinent features. The signal is then classified using a classifier that is applied in accordance with these features. The careful selection of signal characteristics and the development of reliable classifiers are essential components of this approach's success. Real-time applications and resource-constrained contexts benefit greatly from feature-based approaches, which are especially beneficial in situations when algorithm complexity must be reduced [4].

Although feature-based methods exhibit adaptability to various channel models, they encounter significant limitations, including the weak discriminatory capability of manually crafted features and the constrained learning capacity of conventional classification algorithms [5], [6].

2.2. Advanced Approaches

The remarkable data processing powers of deep learning (DL) have attracted a lot of attention and have been used in many different fields due to the quick development of Artificial Intelligence (AI) technology, which includes radio signal processing for communications. Research on the application of deep learning for AMC is ongoing, with new methods and architectures being put forth to increase classification accuracy and lower computing complexity. In fact, using DL to solve traditional feature-based signal classification problems offers a productive and affordable substitute for AMC. To overcome the current shortcomings of conventional techniques, a number of deep network-based AMC techniques, including deep neural networks (DNNs), convolutional neural networks (CNNs) [7], recurrent neural networks (RNNs), and long short-term memory networks (LSTMs) [8], have been developed. Nevertheless, the over-fitting problem caused by a significant number of network parameters may still have an impact on the effectiveness of these deep learning-based AMC techniques [9].

2.3. Ensemble Learning for AMC

With notable performance across a range of domains, ensemble learning has become a potent paradigm in machine learning. Combining predictions from various models is the idea behind improving overall performance, which improves accuracy and robustness [10]. Because ensemble models can handle the complex and dynamic character of communication signals, they have gained interest in the context of Automatic Modulation Classification (AMC). Ensemble models incorporate information from several sources, which allows them to capture complex patterns present in different forms of modulation and different SNR situations [11], [12]. Several benefits are provided by ensemble models in the context of AMC. They perform well with a variety of modulation styles, adjust well to changes in signal-to-noise ratio, and yield higher classification accuracy results. Innovative architectures and approaches are among the latest developments in ensemble models for AMC. Prominent instances comprise deep learning ensemble models that utilize architectures like recurrent neural networks (RNNs), convolutional neural networks (CNNs), and deep neural networks (DNNs). These models show promise for lowering computational complexity and increasing classification accuracy [13].

Notwithstanding their achievements, there are still difficulties in creating efficient group models for AMC. Achieving the ideal balance between coherence and model variation is essential. Furthermore, there is continuous research being conducted to solve overfitting-related concerns and guarantee that ensemble models are generalizable across various signal circumstances. The progress and difficulties described in the literature on ensemble models in AMC serve as a motivation for the ensemble model that this study proposes. In order to take use of complementary characteristics, ResNet and Transformer neural networks were combined. Existing ensemble models in AMC have gaps and room for development, as shown by a rigorous examination. By combining cutting-edge architectures and improving the ensemble learning procedure for more accurate modulation categorization, the suggested model seeks to close these gaps.

3. THE PROPOSED APPROACH

The new method we present in this section for modulation classification (Figure 1) uses an ensemble of two powerful neural network models: Transformer Neural Network (TNN) and Residual Network (ResNet). One model is tuned to accurately predict signals with low SNRs, while the other model is tuned for signals with high SNRs. The primary objective is to mitigate the challenges posed by varying Signal-to-Noise Ratios (SNRs) by tailoring each model to function well in a given SNR scenario. The goal of the ensemble design is to take advantage of TNN's and ResNet's complementary skills in spatial feature extraction and sequential data handling and temporal relationships, respectively.

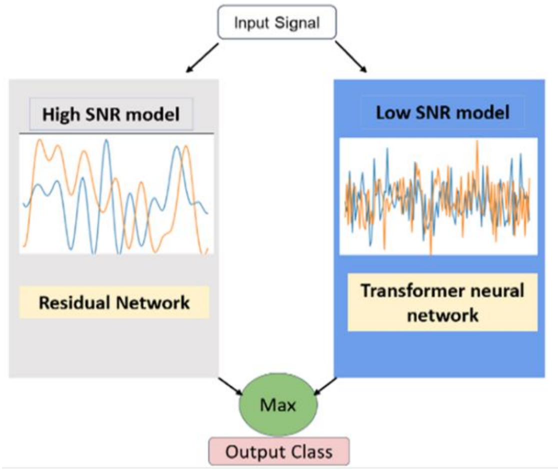

Figure 1. Proposed ensemble model (Resnet with TNN).

3.1. Residual Net: High SNR Model

Microsoft researchers unveiled ResNet, or Residual Network, as a kind of convolutional neural network (CNN) architecture in 2015 [14]. The use of "residual connections," which enable the network to learn a residual mapping rather than an explicit mapping from the input to the output, is the main innovation of ResNet. This allows for much deeper networks to be trained than could previously be achieved without running into the vanishing gradient problem and with acceptable performance. ResNet may be applied to AMC as well as achieving state-of-the-art results on a range of image classification tasks [15].

The residual stack and the residual unit are the two primary components of the ResNet architecture. The residual stack is a series of residual units, each having several levels within it. The residual stack is in charge of using the layer inputs to learn a residual function. To achieve this, first feed the input through the previous layer and then add it to the output of the same layer. It is in charge of deepening the network and enabling it to pick up intricate details from the information. The fundamental component of the ResNet architecture is the residual unit. It is composed of two or more convolutional layers, where the first layer's output is added to the second layer's input.

In addition to helping to preserve data from the source, this enables the network to pick up a residual function. In order to improve the network's stability and normalize the convolutional output, the residual unit additionally contains a batch that normalizes the layer.

3.2. Transformer Neural Network: Low SNR Model

Sequence-to-sequence tasks with long-range dependencies can be solved with ease by the TNN architecture [16]. Transformer models detect the influence and dependency of distant data items by using a series of mathematical operations called attention or self-attention. The network can concentrate on the most crucial components of the signal, such as the signal of interest, and ignore the noise by using attention mechanisms to weight the various input signal components differently. By creating a weighting coefficient to weight the input to sum up for a specific objective, this mechanism's primary job is to identify which features in the input are significant for the target and which ones are not.

There are multiple layers in the Transformer neural network architecture, including encoding and decoding. Multiple layers of feed-forward and self-attention neural networks make up the encoder. When generating predictions, the model is able to balance the significance of various input components thanks to the self-attention process. The output of the self-attention layer is processed using a feed-forward neural network.

Multiple layers of feed-forward and self-attentional neural networks make up the decoder as well. In order to stop the model from "peeping" at future tokens in the input sequence while making predictions, the decoder also employs a technique known as "masked self-attention." Additionally, the transformer architecture has a Multi-Head Attention mechanism that enhances the model's comprehension of the input by allowing it to attend to different sections of the input simultaneously. It is computationally efficient and extremely parallelizable. The following architecture is employed:

- Transformer Block: a 256-node Feed-Forward neural network (FFN) that adds nonlinearity to the model and boosts its capacity.
- The average of every value in the input tensor is called global average pooling.
- Alpha Dropout (0.3): in order to avoid overfitting, a specific percentage of the activations are randomly removed. By leaving the mean and variance of the input at their initial values, it preserves those values.
- Two fully connected networks with an Alpha Dropout of 0.2: Scaled Exponential Linear Unit, or SeLU, is the activation function used.

Due to its ability to handle sequential data, such as time series, and its demonstrated efficacy in tasks requiring comprehension of the context and dependencies among many inputs, the Transformer neural network has been selected for low SNR signals. In fact, our technique consists of extracting features from a low SNR signal using a transformer encoder, and then using those features to reconstruct the signal using a transformer decoder. In order to minimize the error of reconstitution between the input and output signals, the encoder and decoder are concurrently trained.

3.3. Ensemble Model Implementation

The ensemble model put out in this work makes use of the synergies between Transformer Neural Network (TNN) and Residual Network (ResNet), two different deep learning architectures. The purpose of this integration is to take use of TNN's efficiency in managing temporal dependencies and sequential data, as well as ResNet's skill in capturing spatial information.

ResNet performs exceptionally well at differentiating modulation signals in clean, noise-free situations because it is optimized for high Signal-to-Noise Ratio (SNR) environments. ResNet's spatial feature extraction output becomes an essential input for a smooth ensemble integration. With the help of spatial features, the model is trained to generate predictions. On the other hand, the Transformer Network can capture temporal dependencies because it is designed for low SNR conditions and can process sequential data with ease.

The TNN's output, enhanced by its self-attention mechanisms, adds predictions to the ensemble based on signal sequences. Our ensemble model is unique in that it can forecast simultaneously using both ResNet and TNN. Every model processes the incoming signal independently and produces a forecast. Then, using the ensemble decision-making mechanism, the final output is chosen based on which of the two predictions is the maximum. This tactic guarantees that the ensemble gains from the advantages of both models, offering a reliable and flexible classification method. The models are jointly optimized during the ensemble's joint training.

This entails combining the decision-making process that chooses the maximum prediction with the optimization of ResNet and TNN's parameters. The ensemble is a flexible solution since it can dynamically adjust to the many obstacles presented by various SNR situations. The ensemble model is improved architecturally to support the decision-making process and the two forecasts. To preserve the distinct contributions that each ResNet and TNN provide to the overall classification process, further layers and links are added to help with the information flow between them. The ultimate output of the suggested ensemble model is chosen by taking into account the simultaneous forecasts of TNN and ResNet in a unique way. The utilization of a dynamic technique guarantees the ensemble's resilience and ability to leverage the advantages of both models, hence improving the modulation classification accuracy under a range of SNR situations.

4. EXPERIMENTS AND RESULTS

4.1. Dataset Characteristics

In order to verify the effectiveness of our suggested approach, we have assembled an extensive dataset comprising both artificial and actual data. This dataset includes both synthetic and simulated channel effects, and it is thoughtfully constructed to cover a wide variety of modulation settings.

4.1.1. Dataset Structure

The primary components of the dataset are as follows:

- Synthetic Data: To capture the complexity of real-world communication, our synthetic dataset includes twenty-four distinct modulation kinds. Among these are, notably, high-order modulations that are common in high-SNR low-fading channel settings.

- Real Gathered Data: We included 44,876 real-world gathered frames, each of which represented a distinct modulation at a range of noise levels, to further improve the realism of our dataset. Real-world noise presents difficulties that represent real-world communications..

4.1.2. Types of Modulation

Our dataset covers a spectrum of modulation types (See examples in figures 2 and 3), including:

- PSK Modulations: QPSK, 8PSK, 16PSK, 32PSK, 16APSK, 32APSK, 64APSK, 128APSK.
- QAM Modulations: 16QAM, 32QAM, 64QAM, 128QAM, 256QAM.
- Others: AM-SSB-WC (Amplitude Modulation - Single Sideband – Wideband Carrier).

4.1.3. Synthetic Dataset

The following describe the synthetic dataset:

• ***SNR Levels:*** Offering a wide variety of noise situations, each modulation type has 26 levels of Signal-to-Noise Ratio (SNR).

• ***Frame Composition***: 1,024 complicated time-series samples are contained in each of the 4,096 frames that make up each modulation-SNR combination.

• ***Data Format***: In-phase and quadrature (I/Q) floating-point components are used to represent samples.

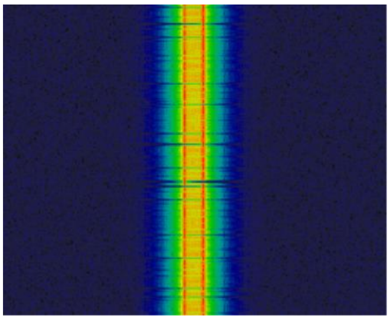

Figure 2. FSK2 modulation.

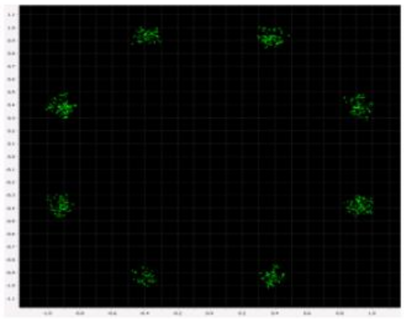

Figure 3. PSK 8 modulation in constellation representation.

4.1.4. Real Dataset

To achieve this goal, we have recorded many real signals via a communications receiver. Then this data has been labeled with its modulation type and level of noise (SNR).

The real dataset introduces authentic challenges:

- **Frame Count:** Containing 44,876 frames, each representing different modulations in thepresence of real-world noise.

- **Classification Challenges:** The noise component in the real dataset enhances thedifficulty of modulation classification, reflecting the complexities encountered in practical applications. Both synthetic and real datasets were thoughtfully merged into a unified dataset of 2,600,780 samples, ensuring a holistic representation of diverse modulation scenarios.

4.1.5. Technical Implementation

All neural network implementations are constructed using Keras, with Tensorflow serving as the backend, ensuring a robust and standardized framework for model development and evaluation. In summary, our dataset composition, structure, and inclusion of both synthetic and real-world data positions it as a robust foundation for evaluating the performance of our proposed ensemble model under varied and realistic conditions.

4.2. Results for high SNR (ResNet)

Following a series of tests, it was found that the high signal-to-noise ratio (SNR) dataset could be classified with nearly perfect accuracy using the ResNet model. The model's maximum accuracy, which it obtained at 30dB, was 95.9% (Figure 4). However, the categorization across low SNR signals was very poor (35% for -4 dB). This is caused by the noise effect and is also connected to specific modulation signals that are undoubtedly harder to categorize because of their unique signal properties.

This deep learning model is resilient and generalizable for predicting high SNR signals rather than those in low SNR situations, as evidenced by the consistency of our results across all test cases (Figure 4). Furthermore, our suggested ResNet-based solution outperforms existing approaches in terms of accuracy when compared to other state-of-the-art techniques for high SNR circumstances.

This demonstrates our method's promise as a dependable solution for high SNR automatic modulation classification challenges.

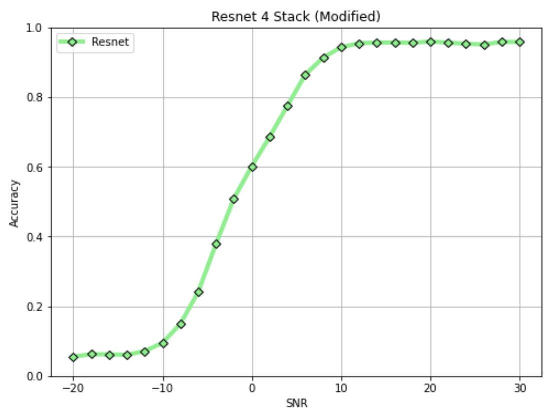

Figure 4. Resnet accuracy versus SNR levels

4.3. Results for low SNR (Transformer network)

After extensive testing under very low SNR settings, the Transformer Network (TNN) demonstrated its remarkable performance. With an exceptional accuracy rate of 72.6%, the model demonstrated a remarkable capacity to both precisely rebuild and identify input signals (figure 5). This result represents a significant improvement over earlier approaches that found it difficult to achieve high accuracy rates under low signal-to-noise ratio circumstances. The Transformer Network is a game-changer in the field of modulation categorization under unfavorable signal-to-noise scenarios because of its effectiveness in such demanding environments.
The Transformer Network's superiority is immediately obvious when compared to the ResNet model, which had trouble recognizing signals in low SNR situations (which varied from -20 dB

to 0 dB) and only managed a maximum accuracy of 20%. This striking difference emphasizes how conventional deep learning models, like ResNet, are inherently limited when it comes to signal processing in low signal-to-noise ratio settings.

The architectural elements of the Transformer Network, including the inclusion of self-attention mechanisms, are responsible for its resilience in low signal-to-noise ratio situations. These processes enable the model to successfully filter out noise while choosing focusing on pertinent components of the incoming signal. The Transformer Network exhibits a distinct resistance to the difficulties presented by low SNR settings by intelligently attending to considerable portions of the signal, which leads to a notable improvement in classification accuracy. Promising implications for real-world applications arise from the Transformer Network's effectiveness in low SNR environments, especially in communication systems where noise interference is a major concern. For modulation classification jobs where signal integrity maintenance in low SNR situations is critical, the model's capacity to maneuver across complex signal environments makes it a useful tool.

Conclusively, the Transformer Network's exceptional low-signal-to-noise ratio performance, when combined with its architectural advantages, represents a noteworthy advancement in the creation of reliable and precise modulation classification models, especially when dealing with difficult noise-filled communication channels.

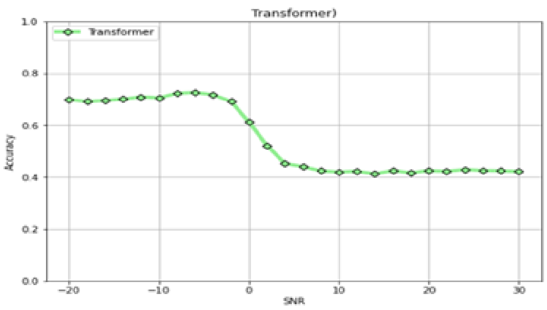

Figure 5. TNN accuracy versus SNR levels

4.4. Results of ensemble model

Figure 6 illustrates the experimental findings of the deep ensemble learning model and provides a thorough understanding of the model's performance throughout a range of Signal-to-Noise Ratios (SNRs). The selected architecture exhibits superior performance for both low and high SNR circumstances, consistently outperforming baseline models [18]. When different SNR circumstances are taken into account, it becomes evident that the suggested ensemble design excels in achieving higher overall accuracy, which is a noteworthy advantage. Figure 6 shows how well the model performs in low SNR settings and validates its effectiveness in high SNR settings.

These results highlight the effectiveness of the ensemble learning strategy in improving the model's accuracy and stability under a range of SNR circumstances. The ensemble model's potential to adapt and perform optimally under various signal difficulties is demonstrated by its persistent ability to outperform individual baseline models. Interestingly, our findings show an interesting trend:

- The ensemble model's classification performance is almost 50% better than the single baseline model, ResNet, at decreasing signal-to-noise ratios (SNR).

- This significant improvement in performance in low signal-to-noise ratio (SNR) circumstances emphasizes ensemble learning's innate ability to reduce noise and enhance classification accuracy in situations where signal clarity is impaired.

- The ensemble model's observed performance has important ramifications for modulation categorization tasks in real-world communication.

- The model's ability to maintain high accuracy across a range of SNR conditions positions it as a robust solution for real-world applications, where signal quality can vary widely.

In conclusion, the ensemble learning model's superior performance across different SNR levels signifies its adaptability and resilience in the face of varying signal challenges. These results strengthen the case for employing ensemble learning as an effective strategy for improving the stability and accuracy of modulation classification models, particularly in dynamic communication environments where SNR fluctuations are prevalent.

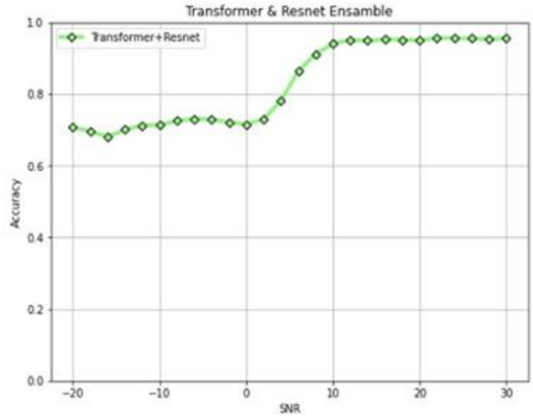

Figure 6. Ensemble learning model accuracy versus SNR levels

4.5. Advantages in Practical Applications

To elucidate the advantages of our chosen models in practical applications, we consider the following factors:

4.5.1. ResNet in High SNR Environments:

- **Acquiring Spatial Features in depth:** ResNet's ability to extract spatial features from high-dimensional data is the foundation of its efficacy in high Signal-to-Noise Ratio (SNR) circumstances. The network is able to recognize complex patterns and structures. ResNet is particularly good at extracting and understanding spatial characteristics in modulation classification tasks with high SNR and little fading. This capacity is essential for correctly differentiating modulation signals in settings that are clear and noise-free.
- **Robust Signal discrimination in Low Noise Conditions:** ResNet exhibits a remarkable capacity to recognize minor differences in modulation signals in clean surroundings with high SNR. When signal clarity is critical, the model's ability to maneuver across complex spatial patterns guarantees a high degree of accuracy in recognizing modulation schemes, adding to its dependability. ResNet is a solid option for applications where the integrity of the transmitted signal is crucial, including in high-quality communication channels, because of its robustness in noise-free environments.

- **Pertinence in Real-World High-SNR, Low-Fading Channels:** ResNet's suitability also extends to high-SNR, low-fading channel settings found in real life. Because of its flexibility in handling different signal complexity, it works well in situations where the signal strength is constantly strong. Because of its flexibility, it can be used more effectively in communication systems where keeping a high signal-to-noise ratio (SNR) is crucial. This means that it can function reliably under situations similar to those seen in stable communication channels.

4.5.2. TNN in Low SNR Environments:

- **Processing Sequential Data accurately:** In low Signal-to-Noise Ratio (SNR) conditions, the Transformer Neural Network (TNN) shows promise as a reliable solution for modulation classification tasks. One of its strongest points is how well it handles sequential data, which is very useful in situations with low signal-to-noise ratios. The attention-based architecture of TNN makes it possible for it to precisely analyze sequential input signals, which facilitates the efficient extraction of temporal connections.
- **Adaptability to Real-World Noisy Communication Channels:** Noise- and interference-filled real-world communication channels can benefit from TNN's capability for modulation classification under low SNR circumstances. Because of its attention mechanisms and capacity to handle sequential data. The model's flexibility in these kinds of noisy communication channels emphasizes its applicability in real-world situations where signal clarity varies.
- **Selective Focus on Relevant Signal Components***:* The ability of TNN's unique attention mechanisms to selectively focus on pertinent portions of the input signal gives the model this ability. TNN's capacity to identify and rank informative signal portions is useful in low SNR environments, where noise can obscure important signal components. This narrow focus makes the model more resilient to noise interference and improves its classification accuracy for modulation schemes in difficult, low signal-to-noise ratio settings.

5. CONCLUSION

With the advancement of Artificial Intelligence, encompassing Deep Learning, neural networks, and other technologies, automated modulation classification (AMC), a fundamental component of communication signal processing, has become more and more important in fields like cognitive electronic warfare and cognitive radio (CR). Its main objective is to correctly categorize the received signals' modulated modes. This research presents an end-to-end deep learning model for classifying modulation signals that integrates the prediction ability of many features and improves model stability through the use of an ensemble learning network. Techniques for ensemble learning are frequently used to handle multi-class classification issues and improve classification accuracy overall. These techniques function by making features more functional and by highlighting each model. In order to create a solid algorithmic framework with great adaptability, our method involves utilizing the advantages of two deep learning architectures, ResNet and Transformer network, and learning from one another. Our tests showed that the suggested deep ensemble approach achieves good stability and accuracy for both high and low SNR categorization recognition.

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