COMMUNICATION SIGNALS MODULATIONS CLASSIFICATION BASED ON NEURAL NETWORK ALGORITHMS

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ABSTRACT

This paper aims to find an automatic solution for the modulation's classification of different types of radio signals by relying on Artificial Intelligence. This project is part of a long process of Communications Intelligence looking for an automatic solution to demodulate, decode and decipher communication signals. Our work therefore consisted in the choice of the database needed for supervised deep learning, the evaluation of existing techniques on raw communication signals, and the proposal of a solution based on deep learning networks allowing to classify the types of modulation with an optimal ratio (computation time / accuracy). We first carried out a research work on the existing models of automatic classification in order to use them as a reference. We consequently proposed an ensemble learning approach based on tuned ResNet and Transformer Neural Network that is efficient at extracting multi- scale features from the raw I/Q sequence data and also considers the challenge of predicting in low Signal Noise Ratio (SNR) conditions. In the end, we delivered an architecture that is easy to handle and apply to communication signals. This solution has an optimal and robust architecture that automatically determines the type of modulation with an accuracy up to 95%.

KEYWORDS

Automatic modulation classification, Modulation recognition, Artificial Intelligence & Deep Learning

1. INTRODUCTION

Communication signals, marked by diverse modulations to achieve high data rates while mitigating interference, present a formidable challenge for Intelligence Systems tasked with monitoring the communications spectrum. As the complexity of modulations increases, the identification and demodulation processes become progressively intricate, particularly for extracting valuable information in the realm of Communications Intelligence (COMINT).

In the domain of COMINT, where the primary objective is to extract meaningful information, the study focuses on the intricate task of recognizing and classifying modulations in intercepted signals. This is pivotal for understanding the type of transmission and subsequently facilitating the demodulation process. Unlike Electronic Intelligence (ELINT), which predominantly deals with radars, COMINT involves decoding communication signals, whether voice or data.

In the transmission of information through communication signals, modulation is a fundamental process. The information is modulated into a specific frequency, enabling high-speed transmission and overcoming atmospheric attenuation challenges. Intercepting an unknown

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signal within the vast spectrum of communications initiates the Intelligence process, involving measurements of frequency and signal levels. However, the initial and critical challenge lies in determining the modulation used for transmitting the radio signal. Traditionally, intelligence approaches involved employing various demodulators iteratively, a method proven to be slow and ineffective, particularly with modern modulations. The advent of Artificial Intelligence (AI) has significantly transformed this landscape. Automatic classification of modulation types at the receiver has garnered substantial attention in the wireless research community, notably improving spectrum utilization efficiency. Early efforts utilized spectrogram images generated by different modulations and applied Convolutional Neural Network (CNN) architectures. Recent studies have taken a novel approach, leveraging the Inphase and Quadrature signals (I/Q) of the signal— referred to as the ”DNA” of any signal. I/Q data has demonstrated superior performance in automatic modulation recognition compared to traditional approaches. Essentially, any signal comprises two components: the In-phase component (Cosine) and the Quadrature component (Sinus). These I/Q samples describe a complex baseband signal, where the real and imaginary parts are represented by the waveforms I(t) and Q(t).

The complete signal description, $X(t) = I(t)+jQ(t)$, encapsulates the essence of the signal, encoded into a matrix of two rows representing I and Q. This I/Q-based approach proves to be a powerful methodology for modulation classification, providing a comprehensive and effective means of deciphering the intricate modulations present in modern 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 stages of Automatic Modulation Classification (AMC), likelihood-based methods were prevalent. These methods involve the precise derivation of likelihood functions for different modulation types. The fundamental idea is to match the received signal against a set of predefined likelihood functions to determine the most probable modulation type. Likelihood-based methods employ probability theories and hypothetical models to address modulation identification challenges in scenarios with both known and unknown channel information [1]. While these approaches can achieve optimal classification accuracy under the assumption of perfect knowledge of signal and channel models, they demand considerable computational complexity for estimating model parameters [2], [3].

2.1.2. Feature-Based Approaches

In the realm of AMC, feature-based techniques serve as a foundational approach for distinguishing modulation patterns. This method hinges on feature extraction and classifier building, offering a pragmatic balance between computational efficiency and classification accuracy. The fundamental premise is to capture the distinctive characteristics of various signals without the need to intricately derive the likelihood function of the signal. The feature-based approach unfolds in two critical steps: pre-processing the signal and extracting relevant features. Subsequently, a classifier is applied to categorize the signal based on these features. The success of this approach crucially depends on the careful selection of signal attributes and the construction of robust classifiers. Feature-based techniques are particularly advantageous in scenarios where algorithm complexity needs to be minimized, making them suitable for real-time applications and resource-constrained environments [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

Deep learning (DL), with its exceptional data processing capabilities, has drawn extensive interest and been applied in a variety of sectors because of the rapid growth of Artificial Intelligence (AI) technology including radio signal processing for communications. The use of deep learning for AMC is an active area of research, with new techniques and architectures being proposed to improve classification accuracy and reduce computational complexity. Indeed, applications of DL as a solution to conventional feature-based signal classification issues provide an efficient and cost-effective alternative for AMC. Several recent AMC methods utilizing deep networks such as deep neural networks (DNNs), convolutional neural networks (CNNs) [7], recurrent neural networks (RNNs), and long short-term memory networks (LSTMs) [8], have been proposed to address the existing limitations of traditional approaches. However, the performance of these deep learning-based AMC methods may still be affected by the over-fitting issue brought on by a considerable number of network parameters [9].

2.3. Ensemble Learning for AMC

Ensemble learning has emerged as a powerful paradigm in machine learning, demonstrating significant success in various domains. The concept involves combining predictions from multiple models to enhance overall performance, providing improved robustness and accuracy [10]. The application of ensemble models in Automatic Modulation Classification (AMC) has garnered attention due to its ability to address the complex and dynamic nature of communication signals. Ensemble models integrate diverse sources of information, enabling them to capture intricate patterns inherent in modulation types and varying SNR conditions [11],[12]. Ensemble models offer several advantages in the context of AMC. They excel in handling diverse modulation types, adapting to variations in SNR, and providing enhanced accuracy in classification outcomes. Recent advancements in ensemble models for AMC include innovative architectures and methodologies. Noteworthy examples include ensemble models based on deep learning, leveraging architectures such as deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). These models demonstrate the potential to improve classification accuracy and reduce computational complexity [13].

Despite their success, challenges exist in designing effective ensemble models for AMC. Striking the right balance between model diversity and coherence is crucial. Additionally, addressing issues related to overfitting and ensuring the generalization of ensemble models across different signal scenarios are ongoing research areas. The proposed ensemble model in this study draws inspiration from the advancements and challenges outlined in the literature on ensemble models in AMC. The choice of combining ResNet and Transformer neural networks is motivated by the need to leverage complementary strengths. A critical analysis of existing ensemble models in AMC reveals gaps and opportunities for improvement. The proposed model aims to address these gaps by integrating state-of-the-art architectures and refining the ensemble learning process for more effective modulation classification.

3. THE PROPOSED APPROACH

In this section, we present our innovative approach (Figure 1) to modulation classification, leveraging an ensemble of two powerful neural network models: Residual Network (ResNet) and Transformer Neural Network (TNN): one optimized for accurately predicting signals with high SNRs, and the other for predicting signals with low SNRs. The key objective is to address challenges posed by varying Signal-to-Noise Ratios (SNRs) by tailoring each model to excel in specific SNR conditions. The ensemble design aims to capitalize on the complementary strengths of ResNet, proficient in spatial feature extraction, and TNN, adept at handling sequential data and capturing temporal dependencies.

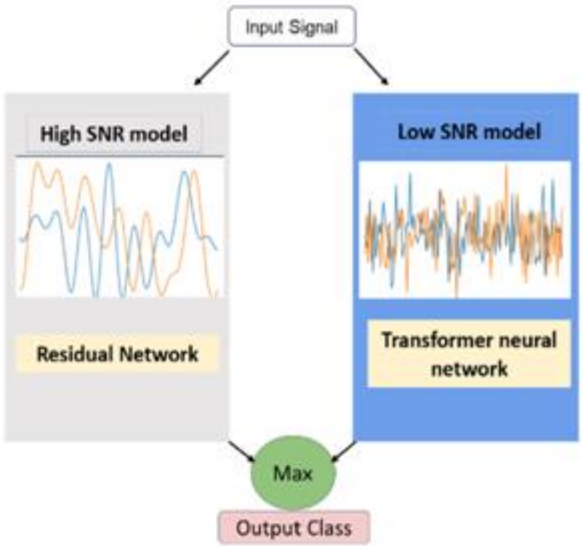

Figure 1. Proposed ensemble model (Resnet with TNN).

3.1. High SNR Model: Residual Net

ResNet (Residual Network) is a type of convolutional neural network (CNN) architecture that was introduced in 2015 by Microsoft researchers [14]. The key innovation of ResNet is the use of" residual connections," which allow the network to learn a residual mapping rather than an explicit mapping from the input to the output. This makes it possible to train much deeper networks than was previously possible, while still maintaining satisfactory performance and without encountering the vanishing gradient problem. ResNet has been used to achieve state-of-the-art results on a variety of im-age classification tasks and can also be utilized for AMC [15].

The ResNet architecture is composed of two main parts: the residual stack and the residual unit. The residual stack is a sequence of residual unit, where each unit contains multiple layers. The residual stack is responsible for learning a residual function with reference to the layer inputs. This can be accomplished by adding the input of a layer to the output of the same layer, before passing it through the next layer. It is responsible for deeping network and allowing it to learn complex characteristics from the data. The residual unit is the core building block of the ResNet architecture. It consists of two or more convolutional layers, with the output of the first layer being added to the input of the second layer. This helps to save information from the source and allows the network to learn a residual function. The residual unit also includes a batch that normalize the layer, which is used to normalize the output of the convolutional and im-prove the stability of the network.

3.2. Low SNR Model: Transformer Neural Network

The TNN is an architecture that is solving easily sequence to sequence tasks in the long-range dependencies [16]. Transformer models apply a set of mathematical procedures known as attention or self-attention, to detect influence and dependency of distant data elements. Attention mechanisms are used to weight the various parts of the input signal differently, which can help the network focus on the most important parts of the signal, like the signal of interest, and disregard the noise. The core function of this mechanism is to determine which features in the input are significant for the target and which features are not by generating a weighting coefficient to weight the input to sum up for a given target.

The Transformer neural network architecture comprises several layers, including encoding and decoding. The encoder is composed of multiple layers of self-attention and feed-forward neural networks. The self-attention mechanism enables the model to weigh the importance of different in- put components when making predictions. The feed-forward neural network is used to process the output of the self- attention layer.

The decoder is also composed of multiple layers of self-attention and feed-forward neural networks. The decoder also uses a mechanism called "masked self-attention" which prevents the model from "peeking" at future tokens in the input sequence when making predictions. The transformer architecture also contains a Multi-Head Attention mechanism, which allow the model to attend to various parts of the input at the same time, improving its ability to understand the input. It is highly parallelizable and computationally efficient. The architecture used is as follows:

- Transformer Block: contains a Feed-Forward neural network (FFN) with 256 nodes, used to increase the capacity of the model by introducing non- linearity.
- Global Average Pooling: average of all the values in the input tensor.
- Alpha Dropout (0.3): which randomly drops out certain proportion of the activations to prevent overfitting. It maintains the mean and variance of the input by keeping them at their original values.
- Two fully connected network along with Alpha Dropout (0.2): the activation function applied is SeLU that stands for Scaled Exponential Linear Unit.

The Transformer neural network has been chosen for low SNR signals as it is able to handle sequential data such as time series, and also it has been shown to be effective in tasks that require understanding the context and dependencies among different inputs. Indeed, our method involves using a transformer encoder to extract features from a low SNR signal, which are then used by a transformer decoder to reconstruct the signal. The encoder and decoder are jointly trained to reduce the error of reconstitution between input and out-put signals.

3.3. Ensemble Model Integration

The ensemble model proposed in this study leverages the synergies between two distinct deep learning architectures: Residual Network (ResNet) and Transformer Neural Network (TNN). This integration is designed to harness ResNet's proficiency in capturing spatial features and TNN's effectiveness in handling sequential data and temporal dependencies.

ResNet, optimized for high Signal-to-Noise Ratio (SNR) environments, excels in distinguishing modulation signals in clear, noise-free conditions. To seamlessly integrate ResNet into the ensemble, its spatial feature extraction output becomes a crucial input. The model is trained to make predictions based on spatial characteristics. Conversely, the Transformer Network is tailored for low SNR scenarios and adeptly processes sequential data, making it suitable for capturing temporal dependencies.

In the ensemble, the TNN's output, enriched with its self-attention mechanisms, contributes predictions based on sequential patterns in the signal. Unique to our ensemble model is the simultaneous prediction capability of both ResNet and TNN. Each model independently processes the input signal and generates a prediction. The ensemble decision-making mechanism is then employed, where the maximum prediction among the two is selected as the final output. This strategy ensures that the ensemble benefits from the strengths of both models, providing a robust and adaptive classification approach. During the joint training of the ensemble, the models are fine-tuned collaboratively. This involves optimizing the parameters of ResNet and TNN while incorporating the decision-making mechanism that selects the maximum prediction. The ensemble learns to dynamically adapt to varying challenges posed by different SNR conditions, making it a versatile solution. Architecturally, the ensemble model is enhanced to accommodate the dual predictions and the decision making process. Additional layers and connections are introduced to facilitate the flow of information between ResNet and TNN, preserving their unique contributions to the overall classification process.

The proposed ensemble model uniquely involves the simultaneous predictions of ResNet and TNN, with the final output determined by selecting the maximum prediction. This dynamic approach ensures that the ensemble is robust and capable of capitalizing on the strengths of both models, ultimately enhancing the accuracy of modulation classification across diverse SNR conditions.

4. EXPERIMENTAL RESULTS

4.1. Experimental Setting: Dataset Selection and Characteristics

To validate the efficacy of our proposed model, we curated a comprehensive dataset that combines synthetic and real-world gathered data. This dataset is carefully designed to encompass a diverse range of modulation scenarios, including both synthetic and simulated channel effects.

4.1.1. Dataset Composition

The dataset consists of the following key components:

- Synthetic Data: Our synthetic dataset incorporates twenty-four different modulation types, reflecting the complexities of real-world communication. Notably, high-order modulations prevalent in high-SNR low-fading channel environments are included.

- Real Gathered Data: To further enhance the realism of our dataset, we incorporated real-world gathered data with 44,876 frames, each representing different modulations at varying noise levels. The presence of real-world noise introduces challenges that closely mimic practical communication scenarios.

4.1.2. Dataset Structure

The dataset is structured as follows:

- Size: In total, our dataset comprises 2,600,780 samples, ensuring a robust representation of diverse modulation scenarios.
- Split: We partitioned the dataset into training (80%) and testing (20%) sets, maintaining a balanced distribution to ensure unbiased model evaluation.

4.1.3. Modulation types

Our dataset covers a spectrum of modulation types (See Figures 3 and 4), 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).

4.1.4. Synthetic Dataset Details

The synthetic dataset is characterized by:

- **SNR Levels**: Featuring twenty-six levels of Signal-to-Noise Ratio (SNR) for each modulation type, providing a comprehensive range of noise conditions.
- **Frame Composition**: Comprising 4,096 frames for each modulation-SNR combination, with each frame containing 1,024 complex time-series samples.
- **Data Format**: Samples are represented as floating-point in-phase and quadrature (I/Q) components.

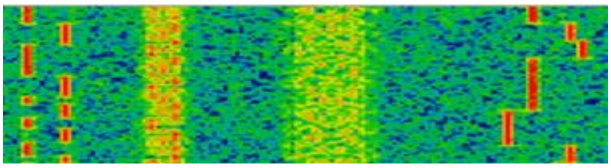

Figure 2. FSK and PSK modulations.

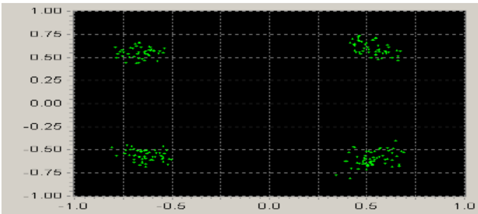

Figure 3. 4 DPSK modulation in constellation representation.

4.1.5. Real Dataset Characteristics

The real dataset introduces authentic challenges:

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

- **Classification Challenges:** The noise component in the real dataset enhances the difficulty 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.

4.1.6. 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)

After conducting various experiments, it was observed that the ResNet model achieved almost perfect accuracy in classifying the high signal-to-noise ratio (SNR) dataset. The highest accuracy attained by the model was 95.9%, which was achieved at 30dB (Figure 5). Nevertheless, the classification over signals at a low SNR was too modest (35% for -4 dB). This is due to the effect of noise, and it is also related to certain modulation signals which are clearly more difficult to classify due to signal characteristics.

The consistency of our results across all test cases indicates that this deep learning model is robust and generalizable for predicting high SNR signals rather than those in low SNR environments (Figures 7, 6 and 8). Furthermore, when comparing our results to those of other state-of-the-art techniques for high SNR conditions, our proposed ResNet-based method surpasses existing approaches in terms of accuracy.

This showcases the potential of our method as a dependable solution for automatic modulation classification tasks in high SNR conditions.

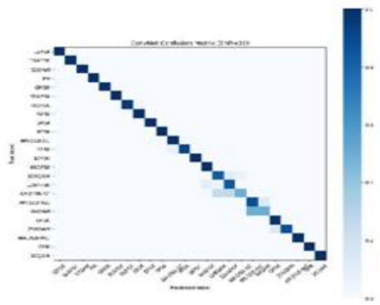

Figure 5. Confusion matrix of the ResNet model at +30 dB SNR.

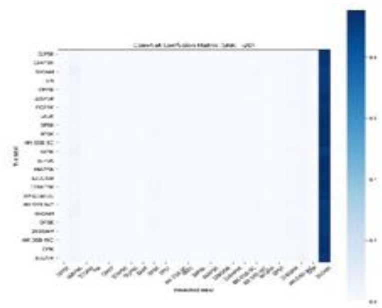

Figure 6. Confusion matrix of the ResNet model at -20dB SNR.

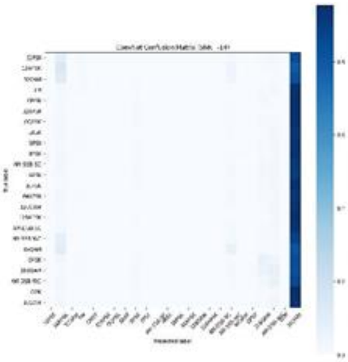

Figure 7. Confusion matrix of the ResNet model at - 14dB SNR.

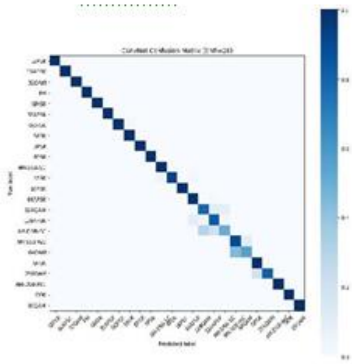

Figure 8. Confusion matrix of the ResNet model at +26dB SNR.

4.3. Results for low SNR (Transformer network)

The Transformer Network (TNN) underwent rigorous testing under challenging low SNR conditions, and the outcomes revealed its impressive capabilities. The model exhibited a remarkable ability to not only reconstruct input signals but also to accurately recognize them, achieving an outstanding accuracy rate of 72.6%. This performance signifies a substantial advancement over previous methodologies that struggled to attain high accuracy rates in low SNR conditions. The Transformer Network's efficacy in such challenging environments establishes it as a breakthrough in the realm of modulation classification under adverse signal-to-noise scenarios. In direct comparison with the ResNet model, which encountered difficulties in detecting signals in low SNR conditions (ranging from -20 dB to 0 dB) and achieved a maximum accuracy of only 20%, the Transformer Network's superiority becomes apparent. This notable contrast highlights the inherent limitations of traditional deep learning models, such as ResNet, when tasked with signal processing in environments with low SNR.

The robustness of the Transformer Network in low SNR conditions can be attributed to its architectural features, particularly the incorporation of self-attention mechanisms. These mechanisms empower the model to selectively focus on relevant components of the input signal while effectively filtering out noise. By intelligently attending to significant parts of the signal, the Transformer Network demonstrates a unique resilience to the challenges posed by low SNR conditions, resulting in a substantial boost in classification accuracy. The success of the Transformer Network in low SNR conditions holds promising implications for real-world applications, particularly in communication systems where noise interference is a prevalent concern. The model's ability to navigate through challenging signal environments positions it as a valuable tool for modulation classification tasks in scenarios where maintaining signal integrity amidst low SNR is crucial.

In conclusion, the Transformer Network's outstanding performance in low SNR conditions, coupled with its architectural strengths, marks a significant stride forward in the development of robust and accurate modulation classification models, particularly in the face of challenging noise-laden communication channels.

4.4. Results of ensemble model

The experimental results of the deep ensemble learning model, depicted in Figures 9, 10, 11, and 12, offer a comprehensive insight into the model's performance across a spectrum of Signal-to-

Noise Ratios (SNRs). The chosen architecture consistently outperforms baseline models, showcasing superior results for both low and high SNR conditions.

The proposed ensemble architecture excels in achieving higher overall accuracy, a notable advantage that becomes apparent when considering diverse SNR scenarios. Figure 11 and Figure 10 depict the model's robust performance in low SNR conditions, while Figure 12 and Figure 9 highlight its proficiency in high SNR environments.

These findings underscore the efficacy of the ensemble learning approach in enhancing the stability and accuracy of the model across varied SNR conditions. The ensemble model's ability to consistently outperform individual baseline models reflects its capacity to adapt and perform optimally under different signal challenges. Notably, our observations reveal a remarkable trend: when the signal-to-noise ratio (SNR) is lower, the classification performance of the ensemble model is approximately 50% greater than that of the single baseline model, ResNet. This substantial performance gain in low SNR conditions highlights the inherent strength of ensemble learning in mitigating the impact of noise and improving classification accuracy when signal clarity is compromised. The observed performance of the ensemble model has significant implications for modulation classification tasks in practical communication scenarios.

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.

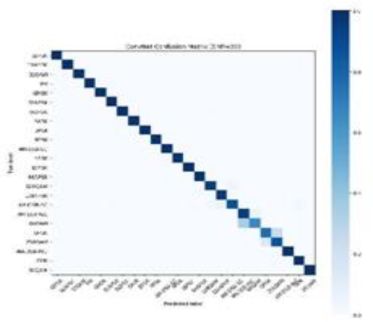

Figure 9. Confusion matrix of the ensemble model model at +30dB SNR.

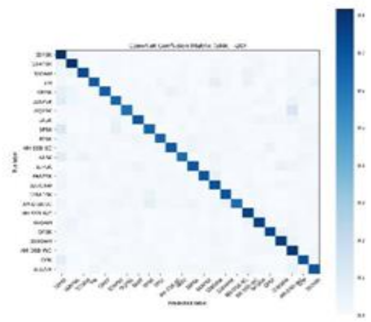

Figure 10. Confusion matrix of the ensemble at -20dB SNR

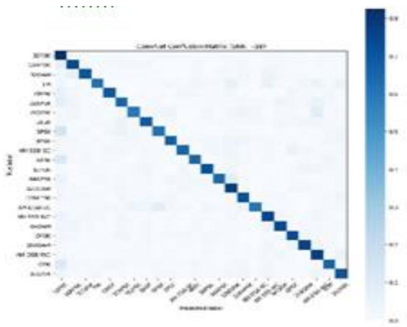

Figure 11. Confusion matrix of the ensemble model at -18dB SNR.

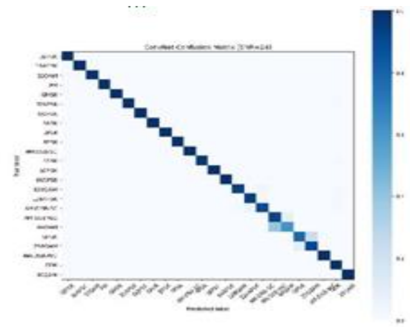

Figure 12.Confusion matrix of the ensemble model at +24dB SNR.

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:

Capturing Spatial Features in Rich Detail:

ResNet's effectiveness in high Signal-to-Noise Ratio (SNR) scenarios is underpinned by its proficiency in capturing spatial features from high-dimensional data. The architecture's unique use of residual connections enables the network to learn intricate patterns and structures in the data. In modulation classification tasks characterized by high SNR and minimal fading, ResNet excels at extracting and interpreting spatial features. This capability is crucial for accurately distinguishing modulation signals within clear, noise-free conditions.

Robust Signal Discernment in Noise-Free Conditions:

In pristine environments with high SNR, ResNet showcases a remarkable ability to discern subtle nuances in modulation signals. The model's capacity to navigate through intricate spatial patterns ensures a high level of accuracy in identifying modulation schemes, contributing to its reliability in scenarios where signal clarity is paramount. The robustness of ResNet in noise-free conditions positions it as a dependable solution for applications where the integrity of the transmitted signal is of utmost importance, such as in high-quality communication channels.

Applicability in Real-World High-SNR, Low-Fading Channels:

Furthermore, ResNet's aptness extends to real-world high-SNR, low-fading channel environments. Its adaptability to varying signal complexities makes it well-suited for scenarios where signal strength is consistently high. This adaptability enhances its applicability in communication systems where maintaining a high SNR is a priority, ensuring reliable performance in conditions akin to those encountered in stable communication channels.

4.5.2. TNN in Low SNR Environments:

Handling Sequential Data with Precision:

The Transformer Neural Network (TNN) emerges as a robust solution for modulation classification tasks in low Signal-to-Noise Ratio (SNR) environments. Its strength lies in its adept handling of sequential data, a characteristic particularly valuable in scenarios marked by low SNR and heightened noise levels. TNN's architecture, based on attention mechanisms, enables it to analyze sequential input signals with precision, allowing for effective extraction of temporal dependencies.

Selective Focus on Relevant Signal Components:

The distinctive feature of attention mechanisms within TNN empowers the model to selectively focus on relevant parts of the input signal. In low SNR conditions, where noise can obfuscate crucial signal components, TNN's ability to discern and prioritize informative sections of the signal proves advantageous. This selective focus contributes to the model's resilience against noise interference, enhancing its accuracy in classifying modulation schemes in challenging, low SNR environments.

Adaptability to Real-World Noisy Communication Channels:

TNN's suitability for modulation classification in low SNR conditions extends to real-world communication channels characterized by noise and interference. Its ability to effectively handle sequential data, coupled with the attention mechanisms, positions TNN as a viable solution for applications where signal degradation due to noise is a prevalent challenge. The model's adaptability in such noisy communication channels highlights its potential for deployment in practical scenarios with varying degrees of signal clarity.

In summary, our choice of ResNet and Transformer Neural Network is informed by a nuanced understanding of their strengths and limitations. While ResNet excels in high SNR conditions, TNN demonstrates superiority in low SNR environments. The ensemble of these models leverages their respective strengths, resulting in a robust solution that exhibits improved stability and accuracy across a spectrum of SNR scenarios.

CONCLUSION

As key part of communication signal processing, automatic modulation classification (AMC) has become increasingly crucial in areas such as cognitive electronic warfare and cognitive radio (CR) with the development of Artificial Intelligence, including Deep Learning, neural networks and others. Its primary goal is to accurately classify the modulated modes of the received signals. This paper proposes an end-to-end deep learning model for modulation signal classification, which uses an ensemble learning network to boost the model's stability and integrate the prediction capacity of several features. Ensemble learning techniques are commonly employed for managing multi-class classification problems and enhancing the overall accuracy of classification. These methods work by improving the functionality of features and promoting each model. Our approach in-volves leveraging the strengths of two deep learning architectures: ResNet and Transformer network and learning from each other to form a robust algorithmic framework with strong adaptability. Through our experiments, we demonstrated that the proposed deep ensemble method achieves high classification recognition accuracy and stability for both high and low SNRs.

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