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Adaptive Signal Detection and Modulation Classification Using CNN and Attention Mechanisms in 6G UAV Systems

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Abstract

In this paper, a signal detection and modulation classification network will be suggested based on an Adaptive Enhanced Signal Detection Network (AERSD) in the 6G UAV communication systems. The central problem that it is based on is that the current methods are very complex and inefficient, especially in low signal-to-noise Ratio (SNR) conditions, in which the existing systems are problematic with efficiency and real-time implementation. The AERSD addresses these barriers by applied use of deep learning algorithms, such as an adaptive 1D Convolutional neural networks (CNNs) being used to extract features, SNR-based parameter optimization to extract specific features, and feature weighting through attention allowing it to adapt to challenging and dynamic communication environments. The system is also lightweight and computationally efficient, and thus can be used in real-time UAV communication. The experimental findings indicate that the AERSD model is better than the conventional signal detection techniques and has an accuracy of 93.75, a recall of 0.92, and a detection rate of 0.972. The model also has a low bit error rate (BER) of 0.00118, a low latency of 0.563 ms, and an energy-efficient model. The ratio of throughput and packet delivery was also analyzed under different conditions of traffic, and it was seen that AERSD is strong enough to handle real-time data. Results confirm the AERSD to be an effective, versatile, and computationally economical tool in signal detection and modulation classification in 6G UAV communication systems.

Keywords: Adaptive Deep Learning, Convolutional Neural Network, Modulation Classification, RF Signal Detection, Signal-to-Noise Ratio, UAV-Based 6G Communication.

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Introduction

The fast emergence of UAV-based 6G communication has made the need to have reliable and intelligent signal detection methods that can be used to perform in dynamic wireless conditions more demanding. The current communication architecture like RIS-enabled networks, ISAC systems, and UAV-assisted communication systems demand effective signal processing to provide the accurate detection and classification of RF signals. A number of works have touched upon the further methods of enhancing communication performance, such as RIS-UAV cooperative networks and optimization approaches to next-generation networks, UAV-to-satellite communication frameworks with deep reinforcement learning, and low-complexity signal detection methods of high-mobility MIMO-OTFS networks. Other studies have concentrated on optimization of intelligent reflective surfaces based on artificial intelligence, the location estimation and target detection frameworks that utilize ISAC, and the use of multi-target sensing techniques in UAV-based networks (Cui et al., 2025).

Moreover, DL models, including CNN-LSTM and localization multidimensional scaling channels estimation models (Nguyen et al., 2023) and (Khalil & Saeed, 2024), have also been explored to enhance the reliability of communication. The significance of intelligent signal processing is also emphasized by radar-based detection models (Xie et al., 2024), STAR-RIS-assisted communication systems (Huang et al., 2025), and channel charting models for UAV navigation (Sun et al., 2025). Nevertheless, most of the current solutions are based on complicated architectures or demand high computing power and thus cannot be applied in real-time UAV communication systems. Additionally, iterative feedback signal detection (Chen et al., 2023), faster-than-Nyquist signal encryption, FPGA-based communication systems, and data-aided channel estimation techniques continue to pose difficulties in terms of adaptability, computation efficiency, and performance in changing SNR settings (Kan et al., 2024). Hence, formulating an effective and dynamic signal detection architecture is an essential research issue in the wireless communication of UAVs.

The proposal of AERSD of 6G communication systems with UAVs is the research proposal to counter the scars of high computational complexity, low responsiveness to dynamical channels, and low fidelity of signal detection in the available solutions (Venugopalan et al., 2025). The RF signals are used in the pre-trained model after which the adaptive 1D CNN layers learn meaningful spectral and modulation features. It implements adaptive manipulation of parameters and weighting of attention that is based on SNR to enhance the performance of detection in changing channel conditions. Last but not least, it is pertinent to state that in identifying signals and categorizing the kind of modulations like BPSK, QPSK and QAM, softmax classification and Adam optimization were helpful (Abbas & Revera, 2025).

This work is driven by the fact that it has been identified that a signal detection framework that can be effectively used in noisy and dynamic UAV-based 6G communication conditions can be of high benefit, as the current approaches have been characterized by excessive computing power requirements and low accuracy. To solve these problems, this research suggests the use of the AERSD to detect RF signals robustly and classify the modulation of signals. The most important aspect is that the adaptive 1D CNN feature extraction, SNR-based parameter adjustment, and attention-based feature weighting have been incorporated to enhance detection performance. Also, an Adam and cross-entropy loss lightweight architecture can be used to detect signals in the UAV communication systems with accuracy and in real time.

Organization: Section 1, the introduction and motivation of the research are given. Section 2 explains the background research and examines available studies on signal detection and wireless communication systems. Section 3 explains the intended methodology along with the design of the AERSD and the algorithm that is used. Section 4 shows the performance evaluation and the results of the experiment. Section 5 gives a discussion of findings and analysis of signal detection techniques in a wireless environment. Lastly, Section 6 provides a summary of the research and research direction.

Background Study

Olickal & Jose, (2023) researched signal and channel state estimation on the wireless communication system based on the use of OFDM. To enhance the signal estimation accuracy, the authors suggested the LSTM projected layer neural network. The model, however, adds complexity in computation and might not be very adaptive to channels that change very fast. It was revealed that it improved accuracy in estimation, but there is still a gap in the research to establish lightweight models to detect wireless signals in real-time (Han et al., 2025).

Zhang et al., (2023) explored the aspect of stealthy jamming detection in wireless communication systems with the assistance of UAVs (Khan et al., 2023). The authors developed an HMM-based detector model to detect jamming

attacks on links of UAVs. The strategy can, however, encounter difficulties in the face of highly dynamic interferences and unfamiliar patterns of attack. These findings enhanced jamming detection performance, yet there is a research gap in the development of adaptive DL -based jamming detection models in dynamic UAV communication conditions.

Previous papers investigated the intelligent metasurface systems in the tracking of moving targets and the enhancement of wireless communication performance. The authors have proposed a system of intelligent metasurface control, which is computer vision-based and used to track targets automatically. Nonetheless, the technique needs intricate hardware assembly and intensive computer processing. The findings have shown a better tracking accuracy but there is a research gap on how to develop an efficient and lightweight intelligent control aspect of real-time communication systems.

Xu et al., (2022) researched the detection of the signal in multicarrier wireless-based systems with DL. The authors suggested a system of turbo detection assisted autoencoders based on neural networks and the channel coding method. Nevertheless, the structure has large needs in terms of training data and computational power. Those outcomes enhanced the accuracy of signal detection, although there is a research gap on the design of low-complexity signal detection methods by DL.

Hossain et al., (2024) specialize in 6G wireless networks' secure communication design. To increase spectral efficiency and security of communication, the authors suggested a CP-less multi-user OCDM transceiver architecture. Synchronization problems, however, can occur in multi-user environments. The findings demonstrated better spectral efficiency, yet there is still a research gap to create efficient signal detection and synchronization methods for the next generation 6G communications.

Habibie et al., (2024) focused on addressing the problem of active user detection on wireless IoT networks. The authors came up with a quantum minimum searching algorithm to find active users. The method, however, is based on quantum-inspired computation, which is not easy to execute in real-life systems. The findings enhanced the efficiency of detection, and there is a gap in the field of research concerning coming up with practical DL -based user detection mechanisms in large-scale IoT networks.

Various studies researched cooperative spectrum sensing in cognitive radio networks as an IoT-enabled wireless communication (Balachander et al., 2023). The authors suggested a collaborative sensing deployment model to optimize the use of the spectrum and the accuracy of detection. Nonetheless, the method creates overhead of communication between sensing nodes. The findings enhanced spectral sensing, yet there is still a gap in the research to come up with intelligent signal detection models with minimized overhead and maximized efficiency.

A recent study explored a method of channel estimation and multipath diversity reception in RIS-enabled broadband wireless systems (Biswas & Tiwari, 2025). In an attempt to improve the reliability of the signals, the authors suggested a cyclic-prefixed single-carrier transmission-based channel estimation method. Nevertheless, the method demands proper RIS architecture and sophisticated modelling of the system. These findings enhanced the effectiveness of channel estimation, although there is a gap in the literature in developing adaptive estimation and signal detection methods that are based on learning.

Hassan et al., (2023) proposed DL -based channel state estimation and signal detection in wireless systems with the use of OFDM. The authors implemented a signal detection model by using DL to improve the detection capabilities in noisy settings. This model, however, needs to be conducted with huge training datasets and lots of computing capabilities. The findings enhanced the accuracy of detecting a signal, yet there is still a research gap in developing lightweight and adaptive models of wireless communication systems in real time.

Previous research investigated signal detection in hybrid modulated Faster-Than-Nyquist optical wireless communication. To capture the time signal features, the authors came up with a detection model based on an LSTM attention neural network. The model complexity and training time are, however, very high. The findings revealed the increased accuracy of signal detection, and there is a research gap in creating efficient frameworks of DL-based detection with less complexity.

Maya et al., (2023) investigated distributed signal detection in wireless sensor networks. The authors came up with an asymptotically equal GLRT-based distributed detection system that is used to detect a reliable signal in multiple nodes. The approach can, however, have scalability challenges when dealing with a large sensor network. The findings enhanced the reliability of detection; however, a research gap still exists on how to design scalable intelligent signal detection strategies in a complex wireless network environment.

Table 1: Summary of Signal Detection and Deep Learning Techniques in UAV and Wireless Communication Systems

Author (Year)	Concept	Methods Used	Limitations	Research Gap	Result
(Zhao et al., 2023)	Wireless communication signal detection using ML.	Proposed Extreme Learning Machine (ELM) combined with Autoencoder (AE) for feature extraction and signal detection.	Performance may degrade under highly dynamic channel conditions and noise.	Need for more adaptive DL models for robust signal detection in complex wireless environments.	Improved signal detection accuracy and faster training compared to conventional ML methods.
(Farag, 2023)	Analysis of CNN layers from a signal processing perspective.	Analytical research of CNN convolutional layer design and mathematical modeling.	Does not focus on practical implementation in real communication systems.	Need for efficient CNN architectures optimized for real-time signal detection tasks.	Provides theoretical insights into CNN layer behavior for signal processing applications.
(Costa et al., 2022)	Research on SNR limitations in spectrum sensing.	Analyzed energy detection methods and SNR wall effects in spectrum sensing.	Energy detection performance drops significantly under noise uncertainty.	Need for advanced detection algorithms that can operate effectively at low SNR levels.	Demonstrated the impact of SNR wall on detection probability and sensing reliability.
(Medaiyese et al., 2022)	UAV detection and identification using learning-based methods.	Proposed a hierarchical ML framework for UAV RF signal detection and classification.	Performance depends on availability of labeled training data.	Need for more scalable DL models for UAV signal identification in large-scale environments.	Improved UAV detection and identification accuracy using RF signal features.
(Chen et al., 2022)	Energy optimization for edge devices in UAV-aided communication systems.	Proposed DL -based energy optimization model trained with Adam optimizer.	High computational requirements for training DL models.	Need for lightweight optimization models suitable for real-time edge devices.	Improved energy efficiency and communication performance in UAV-assisted networks.

The table 1 represents the recent studies on the subject of signal detection, DL architecture, and optimization schemes/techniques used in the wireless and UAV communication systems (Praba et al., 2018). Some of the techniques used in these studies to improve the performance of signal processing include extreme Learning machine, CNN analysis, energy detection based on SNR, hierarchical learning models and DL based optimization. However, the negative aspects of noise sensitivity, computing complexity, and lack of real-time flexibility are indicative of the need to introduce more efficient and lightweight adaptive models in order to provide reliable signal detection as a component of dynamic communication environments.

Proposed Methodology

In this section, the proposed AERSD is proposed to detect the signal accurately and classify the modulation in a 6G communication system using a UAV. The methodology contains the entire architecture and procedure of RF communication signal detection in various dynamic channel configurations. It consists of a system architecture roadmap, mathematical formulae of preprocessing, feature extraction, attention weight, and optimization.

Fig. 1 gives a general idea of the proposed AERSD that is to be implemented in the signal detection in 6G communication systems on UAVs. The received RF signals are initially normalized and the signals are given to CNNs in order to extract signal characteristics associated with the same. This is followed by SNR-based adaptation and attention weighting mechanisms to the system in order to enhance the feature representation under varying channel conditions. Finally, the determined features are processed to determine the type of signal and modulation scheme, such as BPSK, QPSK, or QAM, and the determined outcome is received as the output.

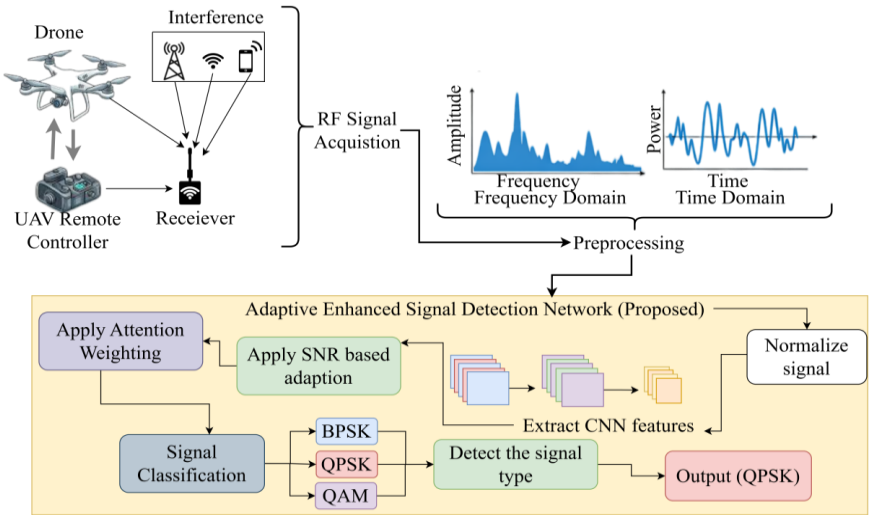


Fig. 1: Overall Architecture for UAV-Based 6G Communication

Adaptive Enhanced Signal Detection Network (AERSD)

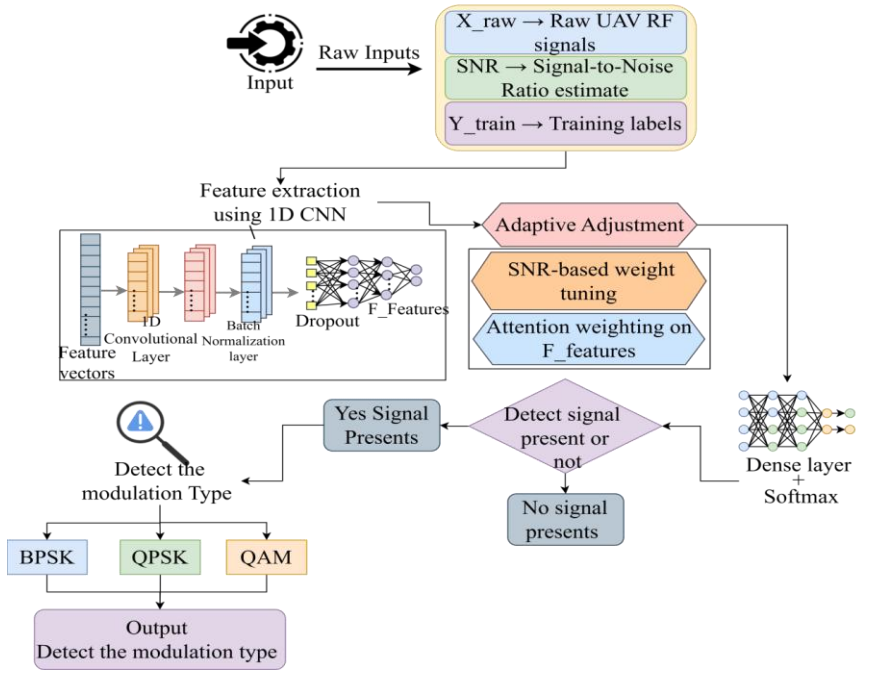


Fig. 2: Adaptive Enhanced Signal Detection Network Architecture

AERSD is a network that recognizes and classifies communication signals in a 6G environment using UAV, and it comprises several stages of processing, interconnected with each other. The algorithm gathers the raw RF signal sample on the receiver of the UAV first and applies noise-aware pre-processing, e.g., normalization, filtering, and feature scaling to minimize the channel distortion. Adaptive DL layers (Medaiyese et al., 2022), which are predominantly 1D CNNs (Farag, 2023) with batch normalization and dropout, are then used to process the processed signals to yield meaningful signal features such as spectral patterns and modulation features. The mixture of the techniques in the model dynamically adjusts the parameters depending on SNR (Costa et al., 2022) and weighting of the features with regard to attention to facilitate the detection process in the varying channel conditions. The type of modulation or the presence of valid signals is established with the help of a thick classification layer with softmax activation. Some of the tricks that are utilized to optimize the network include Adam optimization (Chen et al., 2022), cross-entropy loss, and early stopping in such a way that may provide stability during the training and improve the accuracy of the training. The architecture may be lightweight so as to establish real-time performance to draw a speedy

inference of the board procedures of UAV with minimal latency. On the inside, it has feature extractions, adjustment of parameters, learning signal patterns, and decision classification. Other techniques that are implemented to make sure that it is possible to replicate the algorithm are standardized preprocessing and fixed training parameters and split of the data. All in all, one can mention that AERSD is a powerful and flexible signal detection that can be used in real-time UAV communication systems.

Fig. 2 converts raw radio frequency signals used by the UAV into raw data subjected to a 1D CNN feature extractor and then optimized using an SNR-based adaptive adjustment and attention weighting framework. These weighted features go through a dense layer and softmax activation that initially identifies the presence of a signal and subsequently the type of modulation used, which is in the case of BPSK, QPSK, or QAM. Finally, the system offers a strong framework of automated signal detection and modulation recognition under variable noise conditions.

$$X_{norm} = \frac{X_{raw} - \mu}{\sigma} \quad (1)$$

In equation (1), X_{norm} is the normalized RF signal, which is processed further, and X_{raw} is the original signal captured by the UAV receiver. Parameters μ and σstand to represent the mean and the standard deviation of signal samples, with the help of which the signal values are scaled. The RF signal is standardized with the help of this equation, and scale variations are eliminated prior to feature extraction.

$$F_i = \sum_{k=1}^{K} X_{norm}(i + k).W_k + b \quad (2)$$

This equation (2) F_i stands out as the feature achieved position, wherein X_{norm} is the normalized input signal, and W_k are the convolution filter weights. K is the size of the kernel, and b is the bias applied to the outcome of the convolution. The spectral patterns and modulation characteristics are the most significant signal properties on which this equation might be used to derive these.

$$\hat{F} = \frac{F - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \quad (3)$$

In equation (3), $\hat{F}$is the normalized output of the feature, and F is the output value of the feature obtained after the convolution layer. μ_B And σ_B^2represent the mean and the variance of mini-batch, ϵ in is a small constant to avoid the error of division. This formula is used to stabilize and make neural network training faster.

$$F_{att} = \alpha.F \quad (4)$$

In equation (4), F represents the classification weighted attention feature. Variable F represents the extracted feature vector, and alpha represents the attention weight of the feature that judges the importance of features. The equation is used to highlight the most useful signal properties and enhance the detection performance.

$$P(y_i) = \frac{e^{Z_i}}{\sum_{j=1}^{c} e^{Z_j}} \quad (5)$$

In equation (5), this( ) is the likelihood of the signal being in class i, and Z_i is the score of the class. The number of total classes that are used to classify is denoted by c. The neural network products of this equation are converted into signal detection and modulation classification probabilities.

$$L = -\sum_{i=1}^{C} y_i \log\big(P(y_i)\big) \quad (6)$$

In this equation (6), Lis is the loss value, which is the error in prediction within training. y_i represents the true class label, and $P(y_i)$ is the probability prediction of the softmax. This equation is applied to assess the performance of the classification and to train the model.

$$SNR = 10\ log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \quad (7)$$

Equation (7) SNR is the signal-to-noise ratio that indicates the quality of the signal obtained. This $P_{signal\ \ and\ noise}$ were used to denote the power of the useful signal and the background noise. This formula is applied to the quality of signal measurement and adaptive parameter adjustment.

$$f(x) = \max(0, x) \quad (8)$$

In this equation (8), $f(x)$is the output of the activation function used in CNN layers. This is a variable that represents the input provided as a result of the previous neural network layer. This equation is introduced to bring in non-linearity, enabling the network to learn complex signal patterns.

$$y_i = r_i . h_i \quad (9)$$

In equation (9), $y_i$denotes the final output of neuron i after dropout, and h_i is the original output of the neuron before dropout. $_{Thi}$s is a random binary variable (0 or 1) that denotes whether the neuron remains active or is dropped in the training. Training: In this technique, randomly switches off neurons to reduce overfitting and increase model generalization.

$$\theta_{t+1} = \theta_t - \eta \frac{m_t}{\sqrt{v_t}+\epsilon} \quad (10)$$

In equation (10), θ_t denotes the current parameters in the model, and θ_{t+1}denotes the new parameters after optimization. Where these $\eta$are the learning rate that dictates the size of the update step, m_t and $v_t$were the first and second moment estimations of the gradients. The neural network weights are updated with the help of this equation in an efficient way during training with the Adam optimization algorithm.

Algorithm 1: AERSD

Input:
X_raw: Raw RF signal samples from UAV receiver
SNR: estimate
Y_train: Training labels
Learning_rate, batch_size, epochs: Training parameters
Output:
Signal_flag: Detected signal presence
Modulation_type: Predicted modulation type
Begin
1. Preprocessing
   Normalize X_raw
   Filter noise from signals
   Scale features to reduce channel distortions
   X_processed ← preprocessed signal
2. Feature Extraction
   Pass X_processed through adaptive 1D CNN layers with batch normalization and dropout
   Extract spectral and modulation features → F_features
3. Adaptive Parameter Adjustment
   Adjust network weights and learning parameters dynamically based on SNR
   Apply attention-based weighting to F_features
4. Classification
   Pass F_features through dense layers
   Apply softmax activation
   Signal_flag ← presence or absence of a valid signal
   Modulation_type ← predicted modulation class
5. Training Optimization
   Train the network using the Adam optimizer and the cross-entropy loss
   Implement early stopping to prevent overfitting
6. Real-time Deployment
   Deploy a lightweight trained model on UAV hardware
   Perform fast inference with minimal latency
7. Reproducibility
   Use standardized preprocessing
   Fix training parameters and random seed
   Maintain a consistent dataset split (train/validation/test)

End

The algorithm (1) AERSD processes the UAV RF signals, removes noise and scale features, and extracts significant spectral and modulation features (F features) using adaptive 1D CNN layers. It was weighted adaptively based on SNR and categorized using dense layers based on softmax to determine the existence of a signal and the form of

modulation. The network is efficient on Adam and early stopping, and it is implemented as a lightweight model to predict UAVs in real-time and offer reproducibility with fixed parameters and test/train divisions.

Result

In this results section, the performance of the proposed AERSD model was evaluated through simulation experiments. The entire system and signal processing framework were implemented using the Python programming environment. Several performance metrics, such as accuracy, recall, F1-score, BER, and SNR, were analyzed. The obtained results demonstrate the effectiveness and improved performance of the proposed method.

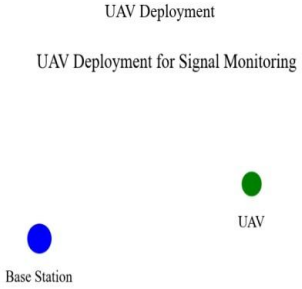


Fig. 3: UAV Deployment



Fig. 4: UAV Searching Signal

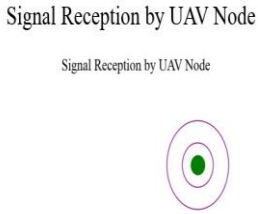


Fig. 5: Signal Reception by UAV Node

Every character plays a significant role in the life cycle of the operation of a UAV-based system of communication.

The first spatial configuration shown in fig. 3 generates the physical distance and the line of sight between the stationary fixed BS and the moving UAV unit. The active discovery stage is shown in fig. 4. At this stage, the active searching will be carried out by the UAV sensors on its onboard device, which is illustrated by the concentric red rings that depict the broadcasting or scanning of the signals. Fig. 5 shows that it has reached a successful handshake stage and that the UAV has already completed searching data, and it is currently getting data as the purple circles on the receivers of a working and stationary communication channel.

These numbers are applied in determining the building of a wireless communication connection between the source and the destination. Fig. 6 in the first stage indicates that the BS is producing a signal of communication, and this is represented by the concentric orange rings emanating from the source. Fig. 7 is the air route through which the signal travels over the distance given between the transmitter and aerial receiver. Fig. 8 shows that the information has been sent successfully, and the directional arrow shows that the signal has been received by the UAV node.

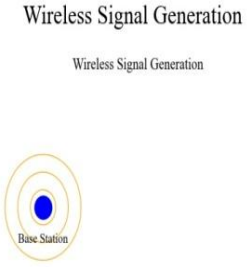


Fig. 6: Wireless Signal Generation

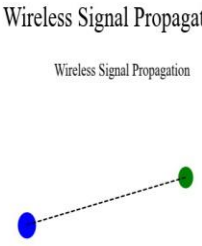


Fig. 7: Wireless Signal Propagation

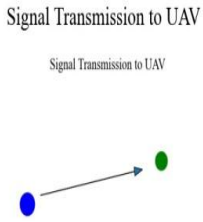


Fig. 8: Signal Transmission to UAV

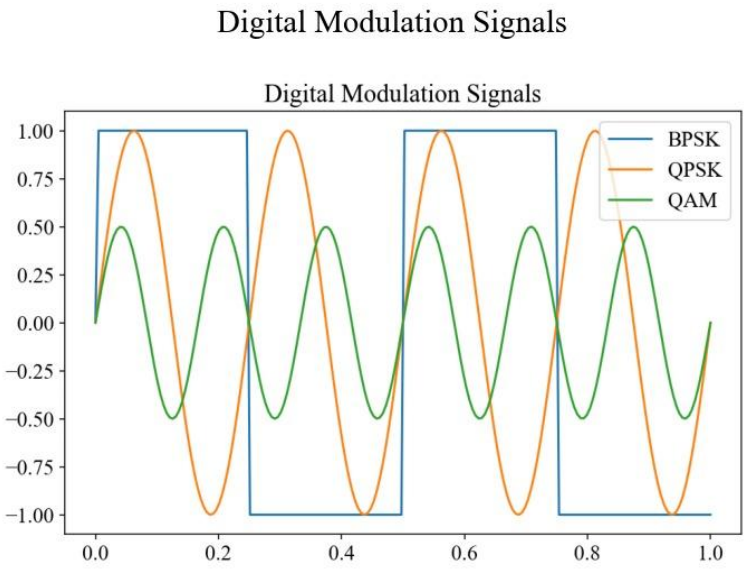


Fig. 9: Digital Modulation signals

Fig. 9 visualizes the time-domain representation of the three largest digital modulation techniques, presenting the phases and amplitude variation of each modulation technique (BPSK, QPSK, and QAM). Unlike the simple square-wave phase shift, which is used to model BPSK, QPSK, and QAM, these waveforms were found to have more complex oscillations, which are the desired waveforms under the AERSD model layer of classification.

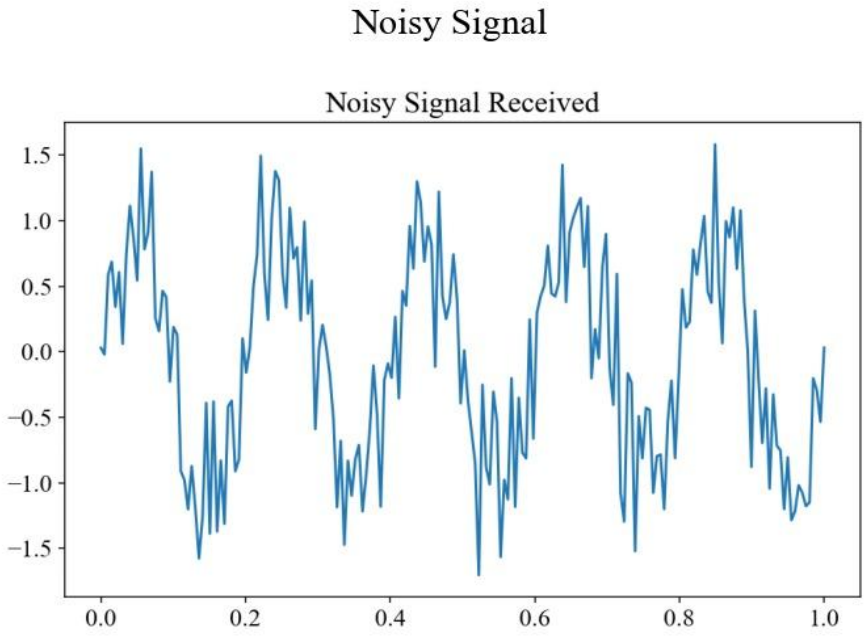


Fig. 10: Noisy Signal

Fig. 10 is a snippet of a captured signal, which is highly corrupted by Gaussian noise, to illustrate the true-life problems that the AERSD model should solve in the bid to capture a great percentage of the signal. The high-frequency signal bursts cover the underlying modulation pattern and to accurately rebuild the original signal information, the SNR-based weight tuning and adaptive adjustment blocks are needed.

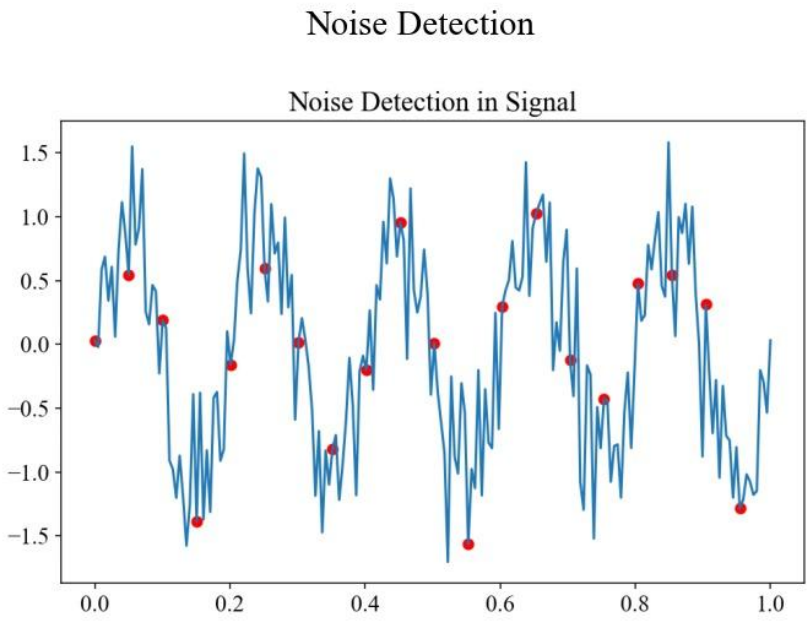


Fig. 11: Noise Detection

This fig. 11 demonstrates the way in which the model is able to detect the definite noise artifact in a corrupted signal, and the red marks are how the peak interference is found. The AERSD can isolate the underlying modulation characteristics of the surrounding noise by identifying these localized distortions which with high fidelity in classification can be done even under the conditions of harsh channel conditions.

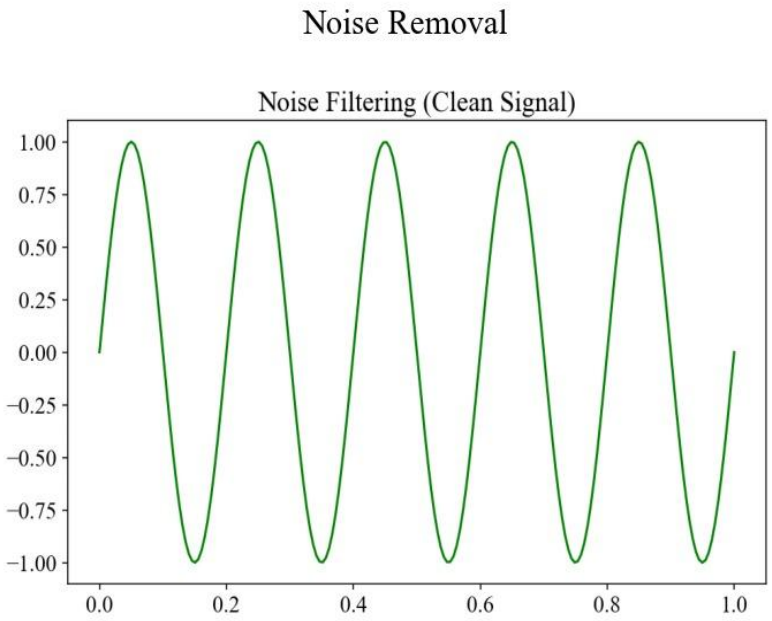


Fig. 12: Noise Removal

A fig. 12 show the filtered waveform with noise removed that has been successfully filtered to obtain the clean signal that has been reconstructed out of the otherwise distorted signal, the input. This smooth waveform is significant to enable the softmax layer to identify the kind of modulation rightly since it is significant to ensure that feature extraction has been performed on the original signal and not at cross-channel interference.

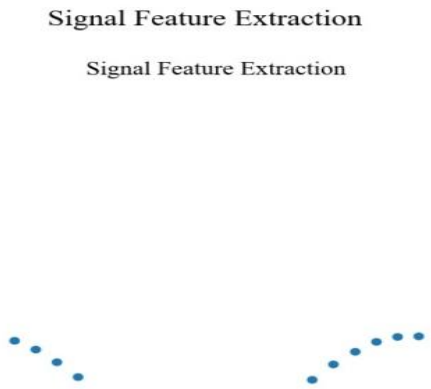


Fig. 13: Signal Feature Extraction

Signal Feature Extraction phase described in fig. 13 entails processing stage of the raw data with the perspective of extracting and isolating significant characteristic patterns. The blue nodes that are sparsely defined are deemed to be the specific data points or features which have been filtered out of the original signal and sent back in order to be able simplify the signal and yet be able to provide the needed information. This is a necessary step in the processing of the signal that will be examined later e.g. a ML model, to recognize or identify patterns.

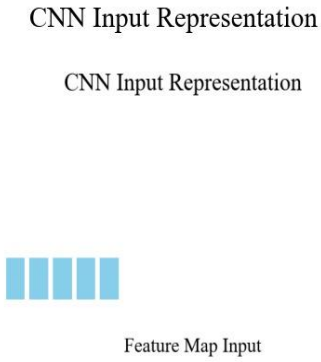


Fig. 14: CNN Input Representation

The provided fig 14 is a first step in a CNN when unprocessed data is fed in the form of a Feature Map Input. It depicts the transformation of the input data, that is, the sequence of blue blocks, into a multi-dimensional array or a multi-dimensional tensor. These blocks denote the patterns, spatial or sequential patterns which are required and will be processed by the network with its hidden layers to obtain features.

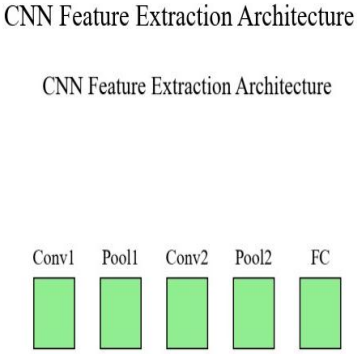


Fig. 15: CNN Feature Extraction Architecture

This fig. 15 illustrates a common CNN Feature Extraction Architecture that consists of Interspersed convolutional and pooling layers and the last layer is a fully connected layer. The CNN layers filter the input data to identify some patterns of the data and the Pool layers are used to drop the unnecessary patterns to maximize the efficiency. These features that have been extracted are then lastly combined into a high-level representation that the Fully Connected layer can then be utilized in either a classification or regression.

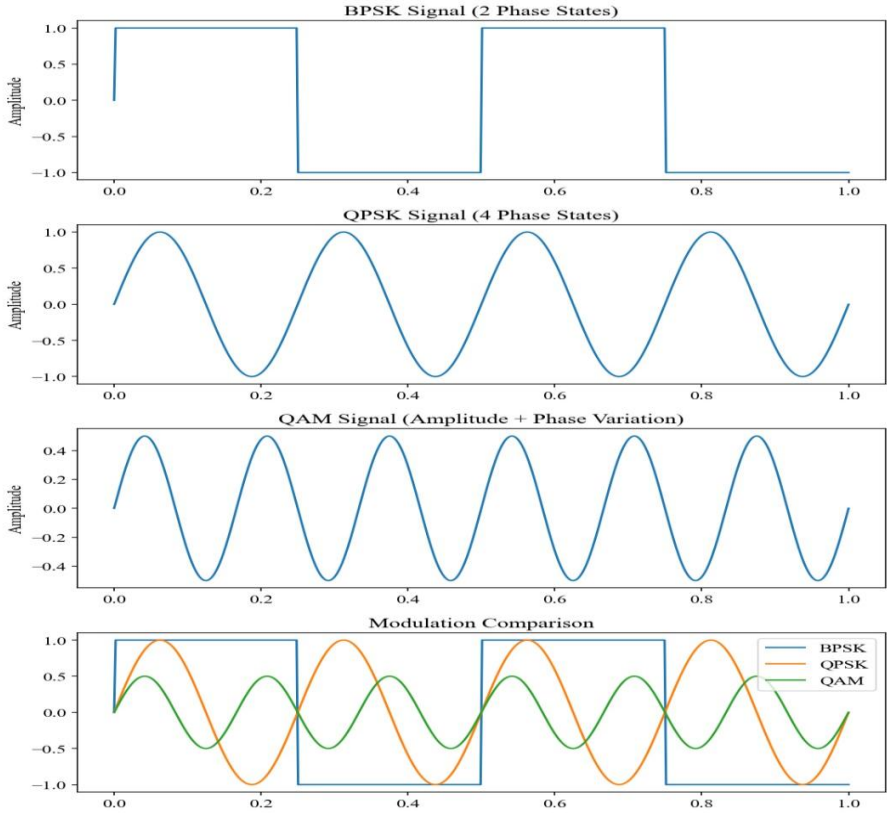


Fig. 16: Comparative Analysis of Digital Modulation Techniques

Fig. 16 is a detailed side-by-side analysis of the BPSK, QPSK, and QAM modulation schemes and a special focus on the unusual form of the amplitude and phase states in time domain. The diagram describes the peculiar properties of the waveforms by plotting each waveform individually and in direct comparison, such properties as discrete phase shifts of BPSK compared to aggregate amplitude and phase shifts of the QAM which AERSD models have been used to make the high-accuracy classifications.

Table 2: Throughput Performance Under Different Traffic Conditions

Traffic Condition	Throughput (Mbps)
Low Traffic	644.0 Mbps
Medium Traffic	368.0 Mbps
High Traffic	92.0 Mbps

This table 2 represents the network throughput in different conditions of traffic. The system has the maximum throughput at 644 Mbps, which is good when the traffic load is minimal, which implies that data transmission is efficient. The throughput reduces as the traffic rises to medium and high levels due to congestion of the network and sharing of the available resources among several devices.

Table 3: Latency Analysis under Different Traffic Conditions

Traffic Condition	Latency (ms)
Low Traffic	0.15 ms
Medium Traffic	0.30 ms
High Traffic	0.45 ms

This table 3 is the latency performance of the network with varying traffic loads. The latency is not only rising, but also it is rising by 0.15 ms to 0.45 ms as traffic increases which means that an increase in network congestion translates to a small increase in transmission delays.

Table 4: Energy Consumption of UAV Nodes

Number of UAV Nodes	Energy Consumption (W)
10 Nodes	25.0 W
20 Nodes	35.0 W
30 Nodes	45.0 W

This table 4 shows the energy usage of UAV nodes with the increase of the network size. There is a proportionate increase in the energy requirement with the UAV node count since more nodes would consume more power to communicate sense and coordinate their activities.

Table 5: Network Capacity with Different UAV Nodes

Number of UAV Nodes	Network Capacity (Devices Supported)
10 Nodes	350 Devices
20 Nodes	700 Devices
30 Nodes	1050 Devices

The table 5 demonstrates the scalability of the network with the UAV-assisted network. The more UAV nodes are on a system the more devices can be connected to the system. The capacity is also increased to 1050 devices, which prove better coverage and network scalability.

Table 6: Packet Delivery Ratio Under Traffic Conditions

Traffic Condition	PDR
Low Traffic	0.98
Medium Traffic	0.96
High Traffic	0.94

This table 6 shows the network reliability and was obtained through PDR. The system has a high PDR of more than 0.94 that withstands high traffic with low packet loss, which is a reliable data transmission.

This table 7 can compare the existing signal detection and learning performance with the proposed AERSD algorithm. The proposed model has the best accuracy (93.75 percent), the rate of detection (0.972) and SNR as well as the lowest rate of BER (0.00118) and delay, thereby showing a better reliability and efficiency in detecting the signal than the current methods.

Table 7: Performance Comparison of Existing Methods and Proposed AERSD Algorithm

Algorithm / Method	Accuracy (%)	Recall	F1 Score	Detection Rate	BER	SNR	End-to-End Delay (ms)
EP-Net (Expectation Propagation Network)	88.6	0.86	0.85	0.91	0.0035	9.8	0.84
GLRT (Generalized Likelihood Ratio Test)	85.4	0.82	0.81	0.88	0.0042	9.2	0.96
ELM-AE (Extreme Learning Machine + Autoencoder)	90.2	0.89	0.88	0.93	0.0026	10.3	0.72
LSTM-Attention Neural Network	92.1	0.91	0.90	0.95	0.0019	10.9	0.64
Multidimensional Scaling (MDS)	84.3	0.80	0.79	0.86	0.0048	8.7	1.02
AERSD (Proposed)	93.75	0.92	0.919	0.972	0.00118	11.42	0.563

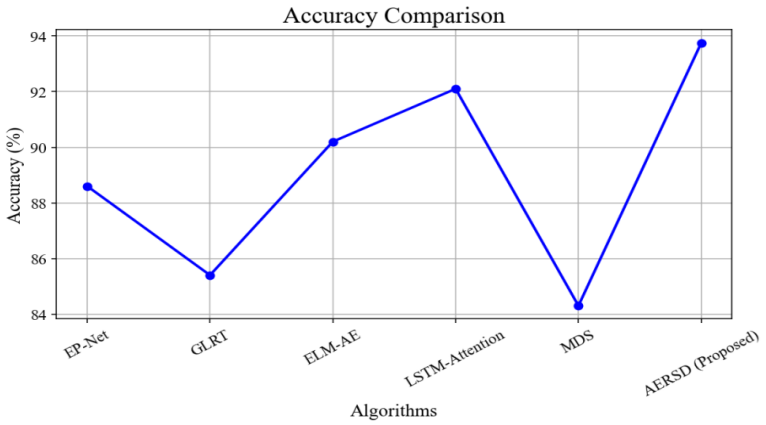


Fig. 17: Accuracy Comparison Chart

Fig. 17 shows a comparison of the accuracy of the six various signal processing algorithms with the AERS model having the best performance at about 93.7 percent. Although classical and DL solutions such as MDS and GLRT score less than 86, the suggested model maintains a better result compared to currently existing solutions such as LSTM-Attention and ELM-AE.

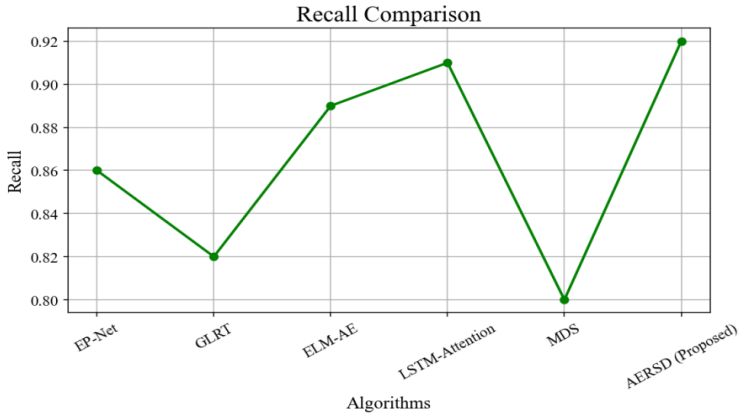


Fig. 18: Recall Comparison Chart

The rate of recall of different algorithms is compared in fig. 18, which shows the highest sensitivity of the AERSD model, which is 0.92. It is much better than the MDS baseline, which reduces to 0.80, demonstrating that the proposed architecture is the most trustworthy one in the case of accurate signal presence detection.

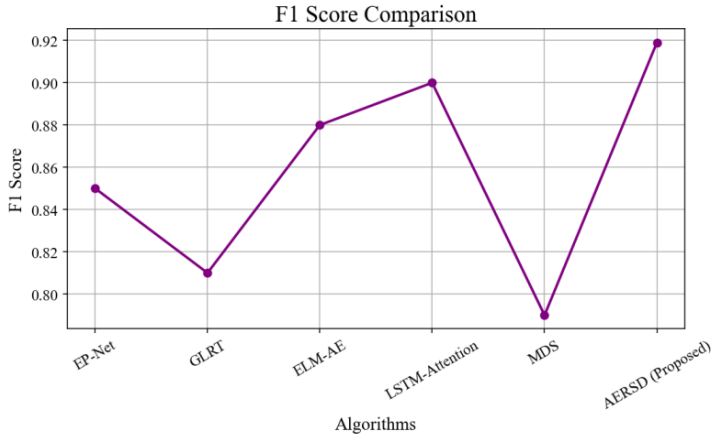


Fig. 19: F1-Score Comparison Chart

The comparison of the F1 scores of the assessed algorithms is presented in fig. 19 and demonstrates the better capacity of the AERSD model to balance precision and recall with the highest score of about 0.92. Although more basic approaches such as MDS and GLRT are unable to ensure a score of more than 0.81, the suggested architecture shows the most consistent general results throughout the dataset.

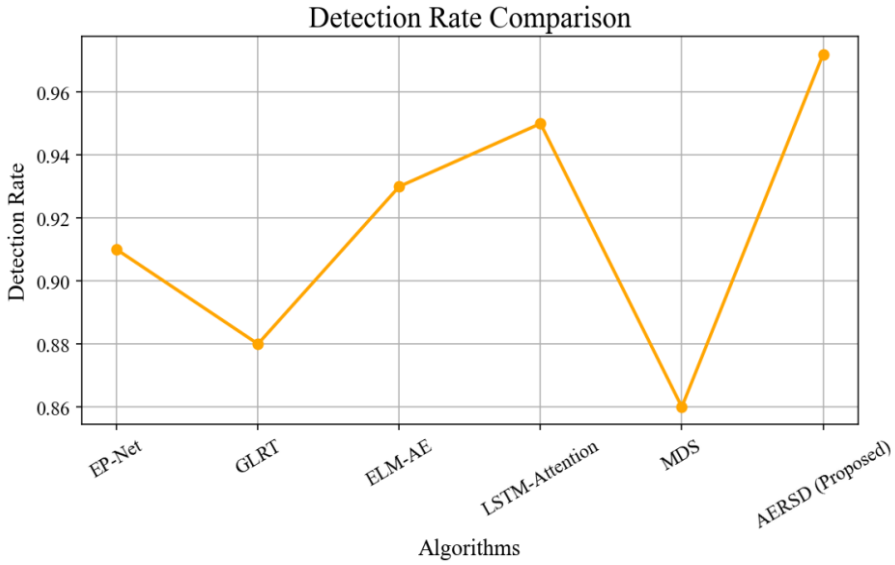


Fig. 20: Detection Rate Comparison Chart

The detection rate performance of different algorithms is shown in fig. 20 and it can be noted that the AERSD model is the most efficient and it is approximately 0.97. It has a huge advantage over traditional approaches such as LSTM-Attention and EP-Net, and MDS algorithm has the poorest detection performance at 0.86.

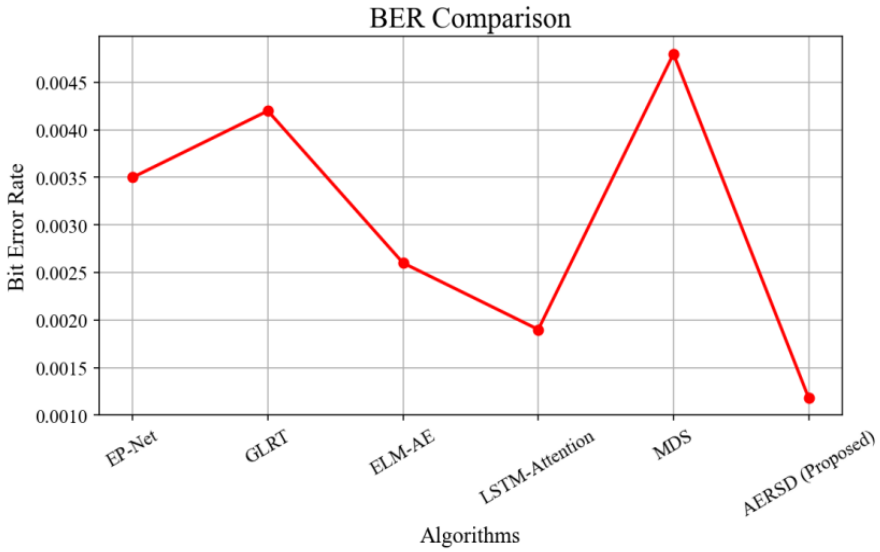


Fig. 21: Bit Error Rate

Fig. 21 compares the errors in the BER of various algorithms and shows that the error rate of AERSD model is the lowest with the magnitude of about 0.0012. Whereas in the preceding metrics, the high the better, the presence of the proposed model at the bottom of the graph indicates that it is more precise when it comes to signal rebuilding than the MDS baseline, which is characterized by the greatest error rate.

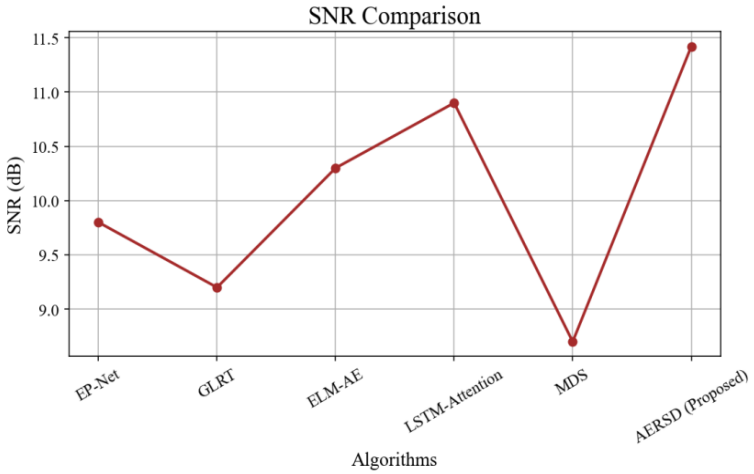


Fig. 22: Signal to Noise Ratio

In fig. 22 indicate that the AERSD model has the highest effective SNR of about 11.4 dB. It shows an obvious benefit over conventional solutions such as GLRT and MDS that cannot operate with low SNR values, suggesting that the suggested model is much more resilient to noisy communication scenarios.

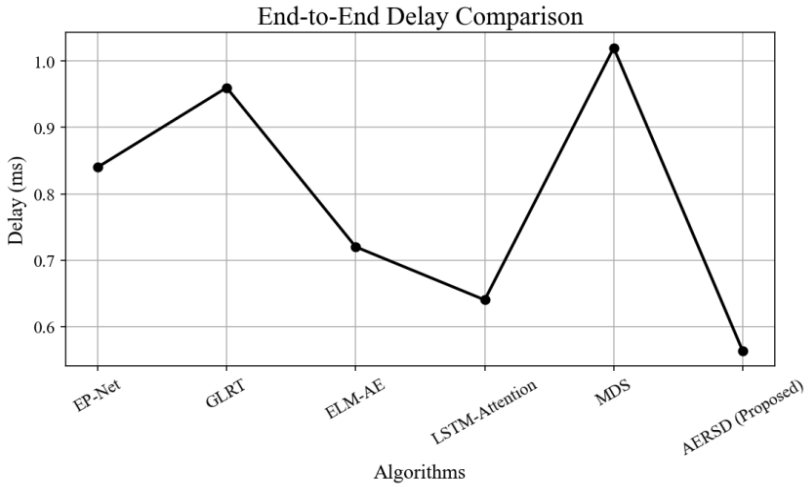


Fig. 23: End-to-End Delay Comparison

Fig. 23 analyses the end-to-end delay of various algorithms indicating that the AERSD model has the lowest latency of about 0.56 ms. Although such conventional approaches as MDS demonstrate maximum delay of more than 1.0 ms, the proposed architecture has the least processing time, and it is the most effective to consider the real-time communication between UAV and ground.

Discussion

The discussion section is dedicated to the exploration of the main peculiarities of the signal detection methods and DL methods applied in the contemporary wireless communication systems. It emphasizes on the utilization of smart models in order to advance signal processing in chaotic and noisy communication environments. This part also examines the major issues and limitations of the currently available methods of detection in the wireless networks.

Signal Detection Techniques in Wireless Communication

Signal detection is very important in providing reliable communication in the contemporary wireless networks. Some researchers have taken into account ML and DL techniques to enhance signal detection in the varying channel conditions. Autoencoders, the LSTM network, and statistical detection models have generally been applied in communication signal research. Such resolutions show that smart models can make a great contribution to the detection and categorization of the indicators in the problematic wireless systems.

Deep Learning Approaches for Communication Systems

The current research shows that DL models are important in enhancing signal processing in wireless communication systems. CNN, recurrent neural networks and hybrid models have been used in feature extraction and signal classification. The techniques allow complex signal pattern learning to be done automatically without feature engineering. Nonetheless, most DL algorithms are very computationally expensive and have large training requirements, thereby limiting real-time implementation in systems.

Challenges in Noisy and Dynamic Communication Environments

The wireless communication environments are usually characterized by noise, interference as well as unstable signal conditions which influence the signal detection performance. Low signal to noise ratio, multipath fading and channel distortion are some of the factors that complicate the process of making reliable detection. Some of the studies discuss why there is need to have strong detection mechanisms that are able to hold the performance even in extreme noise conditions. The need to solve these challenges is still a significant research focus on enhancing the reliability of wireless communication systems.

Conclusion

The study presents an improved AERSD (Adaptive Enhanced Signal Detection Network) architecture, which serves as a suitable solution to signal detection and modulation classification in UAV-assisted 6G communications. It deals with major issues related to low signal-to-noise ratio (SNR), high computational complexity and real-time process requirement in dynamic communication networks. To adjust to the rapidly changing conditions, AERSD incorporates the deep learning methods such as adaptive 1D Convolutional Neural Networks (CNNs), SNR-based parameter optimization, and attention-based weighting of features to guarantee efficient and correct signal detection. The evaluation of performance demonstrates that AERSD is better than current techniques, such as EP-Net, GLRT, and other deep learning models. The model attains 93.75 accuracy, 0.92 recall and 0.972, which is much higher than the current technique outcomes. Also, the low bit error rate (0.00118) and the low latency (0.563 ms) of the model render it appropriate to the real-time UAV-to-UAV communication system. The compact form factor makes it capable of running with few computation costs that allow deployment in limited resource-based UAV settings. The AERSD model also exhibits good performance in change of traffic conditions, throughput, energy efficiency, and the packet delivery ratio (PDR). These findings highlight the effectiveness and stability of the model under various working conditions, which adds to its relevance when 6G UAV communications are involved. Future development will be directed at increasing AERSD capacity in the range of the more complex modulation schemes and larger scale systems. The scalability and generalization enhancements are going to be a necessity in guaranteeing its flexibility to various communication settings. Also, more studies on the improvement of adaptive mechanisms and deep learning technologies will assist in optimizing AERSD to real-time use. Finally, AERSD offers a good prospect of improving signal detection and modulation classification in the 6G communication system to facilitate the development of the UAV-based communication networks.

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