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Automatic Modulation Recognition of DVBS2X Signals

[1] **Dnyanda Hire,** [2] **Suraj Vibhute,** [3] **Sakshi Yeola,** [4] **Shivam Madankar,**

[1]Assistant Professor Electronics and Telecommunication Engineering, Dr. D Y Patil Institute of Engineering Management and Research, Pune, India
[2]Student, Electronics and Telecommunication Engineering, Dr. D Y Patil Institute of Engineering Management and Research, Pune, India
[3]Student, Electronics and Telecommunication Engineering, Dr. D Y Patil Institute of Engineering Management and Research, Pune, India
[4]Student, Electronics and Telecommunication Engineering, Dr. D Y Patil Institute of Engineering Management and Research, Pune, India

Email- [1]dnyanada.hire@dypiu.ac.in , [2]surajvibhute4dec2002@gmail.com , [3]sakshiyeola262@gmail.com , [4]shivammadankar50@gmail.com

Abstract: *This paper provides the comparison between two deep learning methods of automatic modulation recognition of difficult DVB-S2X satellite signals. One way is based on the utilization of a convolutional neural network trained over a broad scope of radio data. The other is based on a hybrid CNN-Transformer model, which was trained on a special simulated dataset created specifically to train on modulations of high throughput of DVB-S2X. We aim at establishing which one is more effective in identifying the advanced modulation schemes at very low signal-to-noise ratio.*

The traditional CNN makes use of one-dimensional model. It is able to take raw in phase (I) and quadrature (Q) samples. Thereafter, it derives local features of the signal. It was trained based on an MATLAB generated dataset which is based on DVB-S2X. It is targeted at the ability to test its potential in handling high order modulations in satellite systems under simulated channel conditions. This CNN-Transformer hybrid model comprises of the combination of CNN layers to obtain the local features and after that, Transformer blocks using multi-head attention to obtain long-range and global correlations. They analyze the overall system using the RadioML 2016 (RML 2016) set which is a benchmark work in this type of work

The standard CNN implementation using the special DVB-S2X dataset demonstrated good prospects of satellite systems. It had an average accuracy of approximately 88.28% at all the SNR levels and its performance did not deteriorate even in presence of weak signals.

Hybrid CNN-Transformer Results (RML 2016 Dataset):

The CNN-Transformer hybrid model achieved good results on the heterogeneous RML 2016 dataset. The model also gave an average performance of 55.28 percent on all 11 modulation types across the SNR range. It is seen that the CNN and the Transformer elements are effectively coupled, particularly when classifying low or medium SNR signals.

Key Words: *Automatic Modulation Recognition (AMR), Deep Learning, Convolutional Neural Network (CNN), Hybrid CNN-Transformer, DVB-S2X, RadioML (RML 2016), Satellite Communication.*

1. INTRODUCTION:

In the study, the results show that automatic modulation recognition will succeed when there is a balance between model design and tailored training. A basic CNN proves to be effective when it is trained on the data of a single system such as DVB-S2X and has a high level of accuracy. However, when we require a model with a large number of diverse types of signals then a more elaborate hybrid CNN- Transformer is superior- as it generalises more and better represents more of the data.

The mean accuracy of the standard CNN that was trained on the DVB-S2X data was 88.28% at all levels of SNR. This shows that it is performing well in a given area [15]. Conversely, the Hybrid CNN-Transformer that was trained on the larger RadioML 2016 (RML 2016) dataset [18] had a total accuracy of 55.28% with varied modulation schemes. This demonstrates its generalization ability [9], [14], [16].
These findings point to the trade off between the complexity of ornamentation and specificity of datasets. This consideration must be considered in the development of smart receivers to monitor the spectrums and the next-generation satellite systems [1], [3], [5], [21].

2. LITERATURE REVIEW:

This study is due to the growing requirements of powerful Automatic Modulation Recognition (AMR) in the recent cognitive radio systems. It is especially in the case of the M- APSK modulation schemes of high-throughput DVB-S2X satellite communications in low SNR conditions [6], [13], and [16]. Although it is demonstrated that Convolutional Neural Networks (CNNs) are able to achieve a good performance in terms of extracting local features [8], [12], the primary problem lies in balancing domain-specific performance and the architecture and generalization complexity. The trained models Hybrid networks such as CNN-Transformer models. on larger datasets including RadioML 2016 (RML 2016) [9], [14], [16], are typically better at generalizing yet usually lose certain domain-specific information.
This paper critically contrasts these various deep learning techniques to offer useful information on the development of intelligent wireless receivers. It assists in making decisions regarding the model selection, using data, and trade-offs to specialization or generalization [1], [3], [5], [21].

•Paper 1: Improved Automatic Modulation Recognition Using Deep Learning with Additive Attention

El-Haryqy et al. [2], [7] developed an improved replication of the Convolutional Recurrent Neural Network, known as ICRNNA model that employs an additive attention in order to produce a high AMR. Spatial information of raw I/Q signals is obtained as the CNN component. BiLSTM network can learn the temporal dependencies in either direction. The additive method of attention through application of a much better variant of additive attention layer helps the model to focus on the most important things. Normalization and dropout are useful to increase generalization. The accuracy of the model of 63.24 and 65.39 on the RadioML2016.10a and 10b datasets respectively were obtained by running two tests. It also could achieve good results in low SNR conditions as low as -10 dB -4 dB. It is a good technique that requires 0.79 million of parameters and 48.42 MFLOPs. That is why it can be applied in real-time cognitive radio and IoT activities. The performance enhancement of CNN, BiLSTM and attention layers was checked in the ablation study with usage of all three layers combination [11], [20].

•Paper 2: Automatic Digital Modulation Recognition of Satellite Communication Signals

Shaheen et al. [4] have come up with feature-based AMR technique of satellite communications which are intrigued in M-PSK, M-QAM and M-APSK arrangements. The analysis (Sequential Higher-Order Statistics) they perform uses kurtosis against single vs. multi-carrier detection, Power Spectral Density (PSD) to measure the amplitude and the 6 th and 8 th -order cumulant to modulation-categorization. Adaptive SNR provides sound in noisy environments. The highest possible classification rate at a SNR of 0 dB was around 100 percent, and the classification rate at low-complexity was hence commendable as could be used on a large scale in practice in the severe satellite communications problem [6], [10].

•Paper 3: Radio Frequency Interference Detection and Automatic Modulation Recognition Based on Mask R-CNN
Another framework that has been created by El-Haryqy et al. [4] to simultaneously detect interference and AMR in cognitive radio systems is a Mask R-CNN-based framework. The model identifies the type of interference (Chirp, CW, Multi-CW) as well as the modulation format (QPSK, 8APSK, 16APSK, 32APSK) using scalograms as input to the model. ResNet50 and ResNet101 were tested to be feature extractors, with the latter having better results. The system had achieved mAP 0.898 and mAR 0.916 on AMR and mAP 0.946 and mAR 0.954 on interference detection. This two-purpose model has lower computational and hardware needs and can be implemented on FPGA SDR and Xilinx RFSoC boards to run in real time [4], [16].

•Paper 4: DL-AMC — Deep Learning for Automatic Modulation Classification
Rehman et al. [14] proposed a deep learning based DMCA, DL-AMC that attempts to improve the spectrum efficiency by sorting out the modulations in the correct order, especially when it is noisy. The paper highlights the potential of

applying deep neural networks in the place of conventional likelihood- and feature-based methods in order to permit more competence and progress in dynamical environments of signals [6], [13].

3. METHODOLOGY :

Method 1: Feature-Based CNN

i. Dataset Description, Data Collection, and Preprocessing

Method 1: CNN Characteristic Account of the information set, Data gathering and pre-treatment. The method is specialized in the categorization of the kinds of modulation of satellite communications. It operates on a custom DVB-S2X stream incorporating only M-APSK signaling which have been detected at the differing Signal-to-Noise Ratios (SNRs) [6], [8], [15].The data set is likely to be simulated by a DVB-S2X channel, where the conditions of the signals can be varied under controlled conditions. The feature engineering is an important part of the process. As opposed to processing the raw In-phase/Quadrature (I/Q) time-series data, the signals are converted to small feature vectors, each containing roughly 4 to 6 important features. These characteristics are obtained based on Higher-Order Statistics (HOS) like amplitude variance (AmpVar), phase variance (PhaseVar), as well as higher-order cumulants (C4 and C6) [2], [10]. These statistical properties represent the critical properties of the signals and considerably minimize the quantity of data that should be handled. This minimization assists in enhancing the performance of the deep learning models that succeed [4], [12].

ii. Model Selection and Classification

The classification of data is done by simple one-dimensional Convolutional neural network (1D- CNN) since it can be utilized in case of small size of the HOS feature vectors [8], [12]. This 1D-CNN is designed to: Extrapolate non-linear trends in the statistical characteristics. Simple structure can be used to make quick predictions and it could be applied in real time when using satellite receivers. The final thick layers are the ones that receive the features as provided by the network, and transforms them to the likelihood of each of the M-APSK modulation classes [6], [16].

iii. Model Training Details

The training is conducted to ensure the maximum accuracy at all SNRs and guarantees the resilience in the difficult channel conditions [13], [17]. Categorical cross-entropy loss that is used with Adam optimizer is appropriate to multi-class classification. The training is done in several epochs with a validation split, which reduces the effects of overfitting and tracks the performance of generalization [6], [11].

iv. Performance Evaluation

There are two main metrics in evaluation, which include overall classification accuracy and per-SNR accuracy. The per-SNR examination is vital in measuring the dependability of its usage, where high SNR (e.g. 10 dB) accuracy (>85 percent) and low SNR (0 dB or lower) performance are acceptable [14], [16]. This plan shows that the model is applicable to cognitive satellite systems that need a high performances in different noise conditions [1], [3].

v. Future Work

Additional research will be conducted on: on top of preprocessing Addition of a lightweight feature selection mechanism to select the most informative HOS features automatically. Training this specialized CNN architecture on edge devices, such as FPGAs, to verify feasibility in the aforementioned satellite ground systems at real- time [4], [18].

vi. System Architecture Details

The 1D-CNN architecture is specifically structured to process the HOS feature vector input:

Input Layer -

- 1D feature vector of HOS components, e.g., shape (N, 4).

Convolutional Block 1 -

- Conv1D: 32 filters, kernel size = 3, ReLU activation
- Batch Normalization

Convolutional Block 2 -

- •Conv1D: 64 filters, kernel size = 3, ReLU activation
- •Batch Normalization

Pooling / Feature Reduction -

- •GlobalAveragePooling1D: Reduces feature maps to a single fixed-length vector; preserves rotational invariance

Dense Layer -

- •Dense: 128 units, ReLU activation
- •Dropout: 0.5 (for regularization)

Output Layer -

- •Dense: K units (number of M-APSK classes)
- •Activation: Softmax

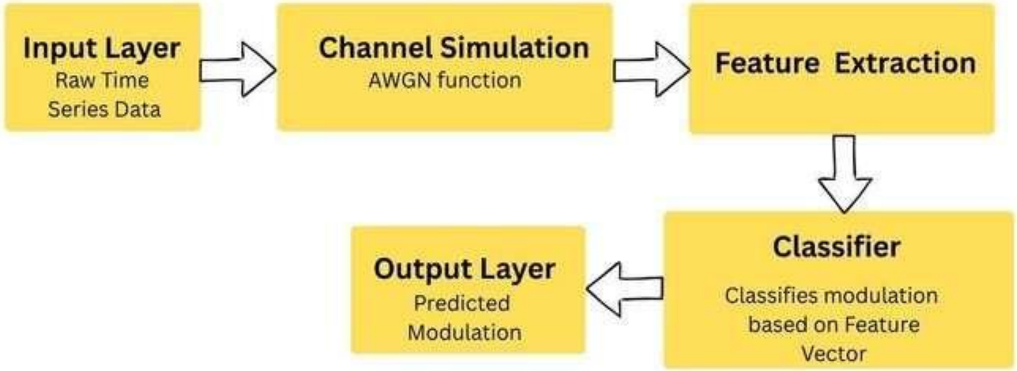


Fig 1.1 : Model Structure for Feature based CNN

Method 2: Hybrid CNN-Transformer for Generalized RML 2016 Recognition

i. Dataset Description

This approach is aimed at the generalized spectrum sensing based on the public dataset of RadioML 2016.10a (RML 2016) of Automatic Modulation Classification (AMC) [18]. It contains 11 types of modulation, both analog and digital, and the channel impairment is realistic and covers a broad SNR range. The model directly takes raw complex time-series data, and its input is In-phase/Quadrature (I/Q) vectors [9], [14].

ii. Augmentation and preprocessing

Having little preprocessing (mostly standardization (zero-mean, unit-variance normalization) of the I/Q samples). The scheme facilitates learning of intrinsic signal properties of the model contrary to engineered inputs [6], [12]. Data augmentation (i.e. added phase or frequency offset) is done during training to enhance robustness and generalization to new channel conditions [13], [16].

iii. Model Selection and Classification

The proposed architecture is Hybrid CNN-Transformer, per which: CNN layers are used to obtain local features in I/Q vectors. Transformer encoder layers indicate world dependence and inter-temporal long-range dependencies. This hybrid architecture is essential to be able to discriminate complex, similar modulation schemes, i.e. 16QAM, 64QAM, which are difficult to differentiate using conventional CNNs only [13], [17].

iv. Model Training Details

End-to-end training of the model is done with Adam optimizer and categorical cross-entropy loss. The sequential modeling of the Transformer makes the learning rate scheduling a careful one. Applied to sustain the stability of gradients during very long sequences. The training goal focuses on generalization, and the ultimate goal of the training is a high total accuracy in all modulation classes, especially at mid-to-high SNRs [14], [16].

v. Performance Evaluation

Performance measures will be macro-average classification accuracy and weighted F1-score, which are trade-off measures of accuracy and recall by potentially imbalanced classes. The confusion matrix is used to take into consideration the classification problems among the modulation families, e.g. PSK, QAM, to make the necessary improvements on the model [10], [12].

vi. Future Work

Future work will focus on:

Further optimization of the hybrid architecture by looking into lightweight self-attention mechanisms to minimize the number of parameters and increase real-time achievability. Applying transfer learning to use the generalized RML 2016 dataset on smaller and specialized datasets to improve sample efficiency and generalization [13], [16].

vii. System Architecture Details

The Hybrid CNN-Transformer architecture is structured in three distinct, sequential stages:

Input Layer -
- Raw I/Q samples (e.g., (N, 2, 128)).

CNN Feature Extraction Block (Local Pattern Learning) -
- Layer 1: Conv1D (Filter size 8, 64 filters, ReLU), followed by BatchNormalization.
- Layer 2: Conv1D (Filter size 5, 64 filters, ReLU), followed by BatchNormalization.
- Output: Generates sequence of local feature embeddings from the raw I/Q data.

Transformer Encoder Block (Global Context Learning) -
- Positional Encoding: Added to the sequence of CNN features to inject order information.
- Transformer Layer (Repeated N times):
  - Multi-Head Self-Attention: Captures long-range dependencies across the sequence elements.
  - Add & Norm: Residual connection and layer normalization.
  - Feed-Forward Network (FFN): Point-wise linear transformation.
  - Add & Norm: Second residual connection and layer normalization.

Classification Head -
- Global Pooling: A global pooling operation (e.g., GlobalAveragePooling1D on the Transformer output) to reduce the sequence to a fixed-size vector.
- Dense Layers: One or more Dense layers for final decision mapping.
- Output Layer: Dense layer with Softmax activation over the 11 RML 2016 modulation classes.

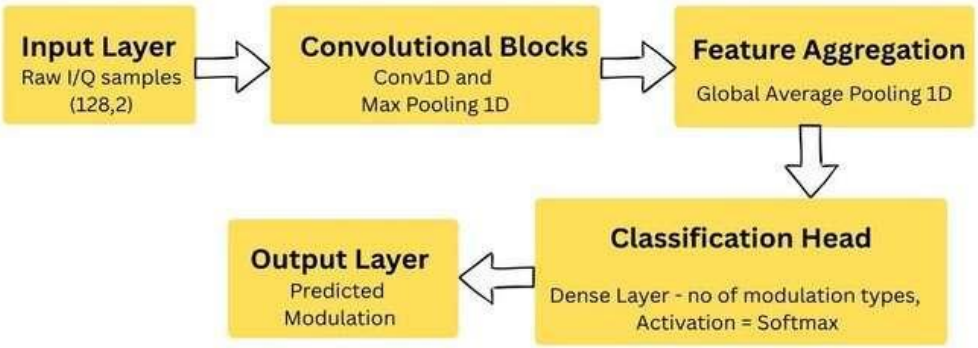


Fig 1.2 : Model Structure for CNN - Transformer

4. RESULTS :

The above experiment demonstrates that the proposed feature-based CNN model performs more efficiently in recognizing the DVBS2X modulations.

Across a range of Signal-to-Noise Ratios from 0 to 20 dB, the model achieved a classification accuracy of 88.28%. This result indicates that the CNN was able to capture the variations in

the modulation patterns using extracted statistical features, including Amplitude Variance (AmpVar), Phase Variance (PhaseVar), and higher-order cumulants C4 and C6.

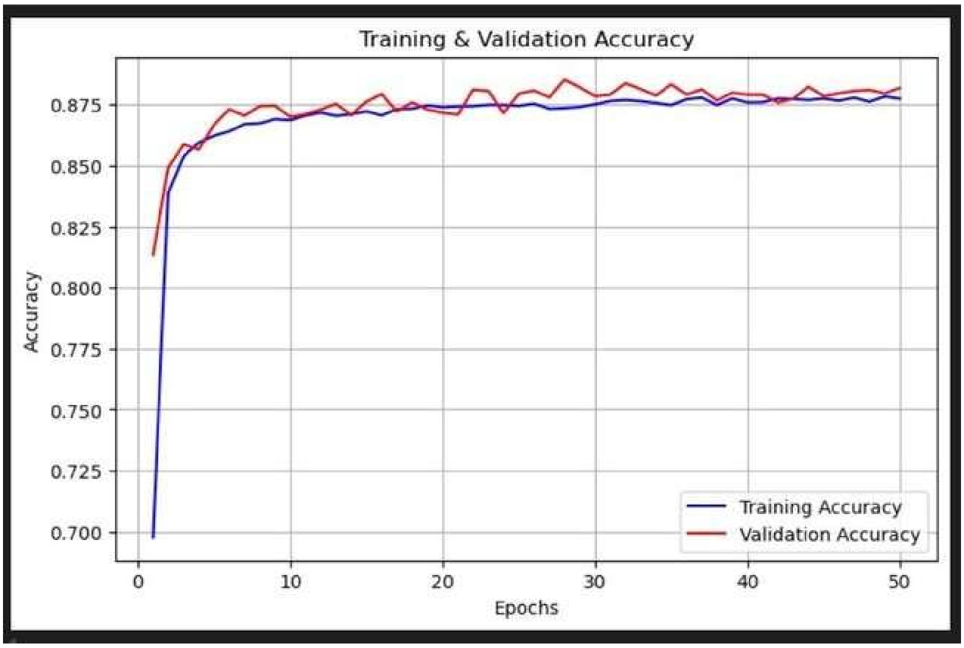
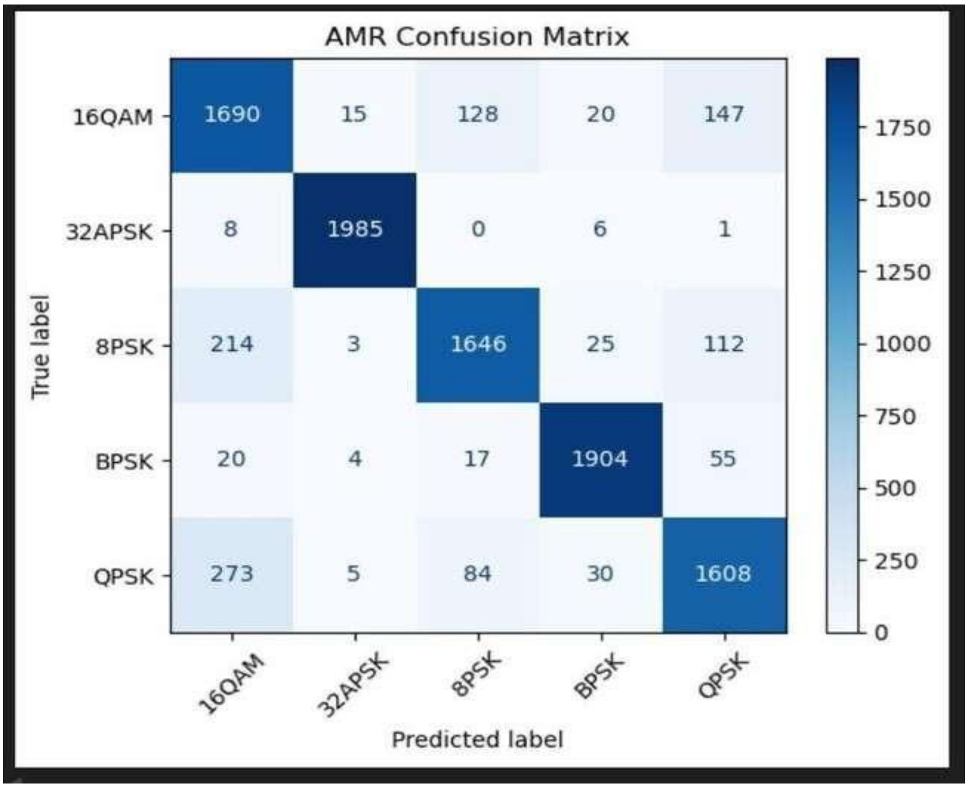


Fig 2.1 : Model Accuracy and Loss for Feature based CNN



True label \ Predicted label	16QAM	32APSK	8PSK	BPSK	QPSK
16QAM	1690	15	128	20	147
32APSK	8	1985	0	6	1
8PSK	214	3	1646	25	112
BPSK	20	4	17	1904	55
QPSK	273	5	84	30	1608

Fig 2.2 : Correlation Matrix for Feature based CNN

In comparison, the Hybrid CNN-Transformer model, which is trained on RadioML2016.10a dataset, achieved a classification accuracy of 55.28% on 11 different modulation categories. Although this model has higher demand in computation than ANN, it showed better consistency and resilience at moderate to high SNR levels (0-10 dB).
The usage of multi-head self-attention improves the capability of the model to learn long- range temporal dependencies in conjunction with learnable parts of the I/Q signals to obtain better overall complex modulation recognition.

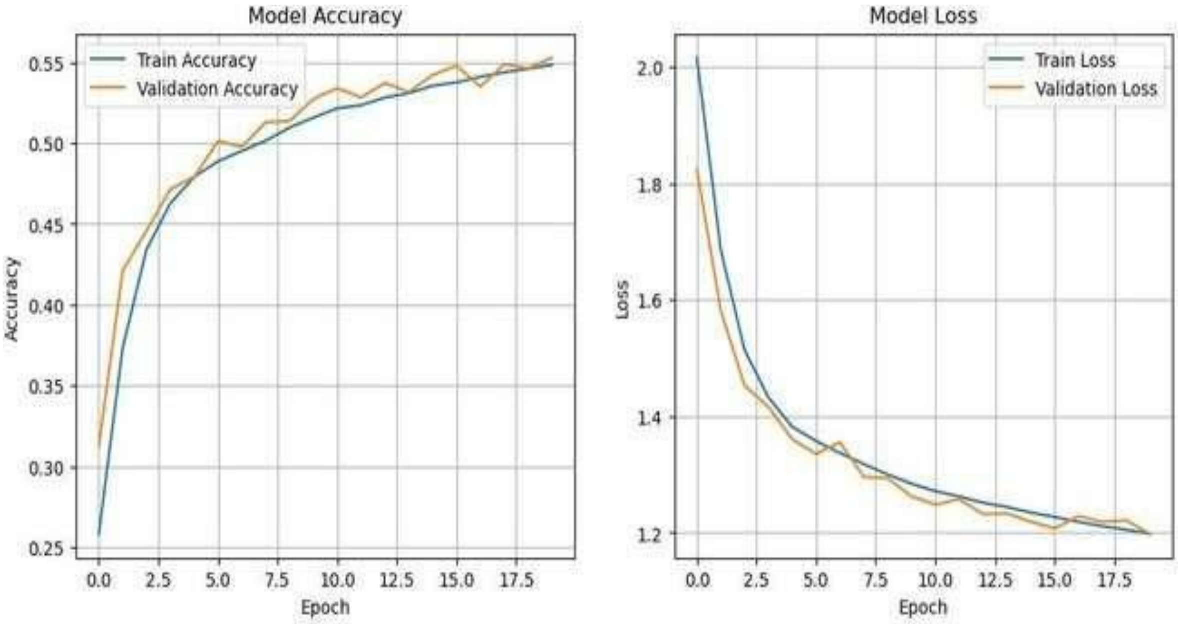
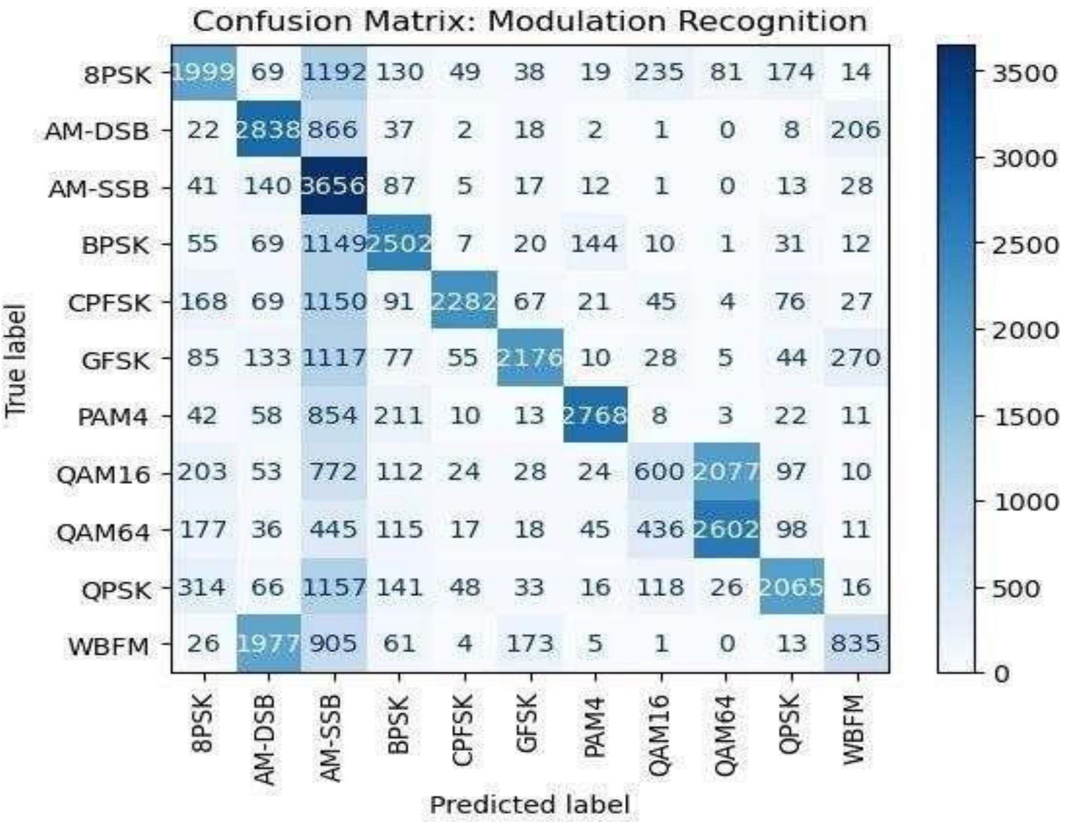


Fig 3.1 : Model Accuracy and Loss for CNN - Transformer



	8PSK	AM-DSB	AM-SSB	BPSK	CPFSK	GFSK	PAM4	QAM16	QAM64	QPSK	WBFM
8PSK	1999	69	1192	130	49	38	19	235	81	174	14
AM-DSB	22	2838	866	37	2	18	2	1	0	8	206
AM-SSB	41	140	3656	87	5	17	12	1	0	13	28
BPSK	55	69	1149	2502	7	20	144	10	1	31	12
CPFSK	168	69	1150	91	2282	67	21	45	4	76	27
GFSK	85	133	1117	77	55	2176	10	28	5	44	270
PAM4	42	58	854	211	10	13	2768	8	3	22	11
QAM16	203	53	772	112	24	28	24	600	2077	97	10
QAM64	177	36	445	115	17	18	45	436	2602	98	11
QPSK	314	66	1157	141	48	33	16	118	26	2065	16
WBFM	26	1977	905	61	4	173	5	1	0	13	835

Fig 3.2 : Correlation Matrix for CNN – Transformer

Model	Dataset	SNR Range(dB)	Accuracy	Key Features
Feature- based CNN	DVB-S2X M-APSK	0 - 20	88.28%	AmpVar , PhaseVar , C4 , C6
Hybrid CNN-Transformer	RadioML2016.1 0a	-20 - 18	55.28%	Multi-head Self-attention, I/Q raw data

Table 1: Overall Review and Results of Models

5. ANALYSIS:

The results showed the outcomes regarding the application of deep learning structures to Automatic Modulation Recognition (AMR). The feature-based CNN was able to attain an accuracy of 88.28 percent on DVBS2X Signals, which indicates that such statistical characteristics as Amplitude variation, Phase variation, cumulants C4 and C6 can be considered effective to reflect subtle differences in modulation, have the strength to be reliable at various levels of signal-to-noise ratios. Conversely, the Hybrid CNN-Transformer scored 55.28 per cent rate on the generalized RadioML2016.10a dataset that comprises 11 types of modulations. The fact is that multi-head self-attention can capture long-range dependencies and therefore it can recognize a various range of broad-spectrum information. It is however more computationally intensive than all the models mentioned above. This simplistic analogy implies a second trade-off: feature-based models can be effective and very precise in domain-specific datasets whereas the generalized hybrid models can be much more effective in a variety of modulations, but at a significantly higher computational cost. In general, the choice of the model must be suggested by the nature of the data and the requirements of the application.

6. CONCLUSION :

The article demonstrates deep learning models are likely to be effective when identifying complex modulations of DVB-S2X. The CNN with the feature-based model was quite effective with the capacity to observe the small statistical features related to the distinctions under varying SNR conditions, but the Hybrid CNN-Transformer model was also useful in generalization to varying modalities through the help of the multi-head attentions to grasp the distant relationship. The specialization and the generalization trade-off come into the limelight in this case. The above results suggest that the choice of the proper model can be conducted in relation to the fields of application, the satellite recognition is more related to the domains when CNNs are applied, and when multiple spectrum monitoring is required, the hybrid models based on the use of Transformers may be implemented. The two methods could be utilized during the design of the both the intelligent and the dependable communication systems.

7. RECOMMENDATIONS:

- Introduce design hybrid processes, i.e. combination of feature based models and end-to-end models so as to be as accurate and economical as possible [13], [16].
- Train noise-resistant and noise augmentation to improve the channel condition reliability in real world conditions [6], [12].
- Develop light models, which can be executed in real-time with the assistance of satellites, handheld devices, or the internet of things [8], [18].
- Transfer learning Transfer learning to scale models enable you to transfer the model to new modulation schemes without training the model on each example [13], [17].
- Combine AMR and intelligent spectrum management in a way that it supports adaptive and automated communications [1], [3].
- Research on the existing paradigm of learning to adjust models based on the cues in changing and varying environments [14], [16].
- Scale down to the low-power and resource-constrained devices to enable factors of scalability and deployment [6], [20].

REFERENCES:

1. S. T., R. S., S. J., J. S. R. Alex, R. G., and M. Das, “Reinforcement learning-based automated modulation switching algorithm for an enhanced underwater acoustic communication,” Results in Engineering, vol. 23, art. no. 102791, 2024.
2. N. El-Haryqy, Z. Madini, Y. Zouine, and A. Kharbouche, “A survey on automatic signal detection using deep learning,” 2023.
3. D. Balakumar and S. Nandakumar, “Blockchain-enabled cooperative spectrum sensing in 5G and B5G cognitive radio via massive multiple-input multiple-output nonorthogonal multiple access,” Results in Engineering, vol. 24, art. no. 102840, 2024.
4. N. El-Haryqy, Z. Madini, and Y. Zouine, “Radio frequency interference detection and automatic modulation recognition based on Mask RCNN,” International Journal of Computer Networks & Communications, vol. 16, no. 5, pp. 23–42, 2024.
5. G. Eappen, S. T., and R. A., “Migration and mutation (meta) hybrid trained ANN for dynamic spectrum access in wireless body area network,” Results in Engineering, vol. 25, art. no. 103883, 2025.
6. L. Li, Y. Zhu, and Z. Zhu, “Automatic modulation classification using ResNeXt-GRU with deep feature fusion,” IEEE Transactions on Instrumentation and Measurement, vol. 72, pp. 1–10, 2023.
7. N. El-Haryqy, Z. Madini, Y. Zouine, and A. Kharbouche, “A survey on automatic signal detection using deep learning,” in Proc. Int. Conf. Optimization and Applications (ICOA), 2023.
8. A. P. Hermawan, R. R. Ginanjar, D.-S. Kim, and J.-M. Lee, “CNN-based automatic modulation classification for beyond 5G communications,” IEEE Communications Letters, vol. 24, no. 5, pp. 1038–1041, 2020.
9. X. Liu, D. Yang, and A. E. Gamal, “Deep neural network architectures for modulation classification,” in Proc. 51st Asilomar Conf. Signals, Systems, and Computers, 2017, pp. 915– 919.
10. W. Lin, D. Hou, J. Huang, L. Li, and Z. Han, “Transfer learning for automatic modulation recognition using a few modulated signal samples,” IEEE Transactions on Vehicular Technology, vol. 72, no. 9, pp. 12391–12395, 2023.
11. J. N. Njoku, M. E. Morocho-Cayamcela, and W. Lim, “CGDNet: Efficient hybrid deep learning model for robust automatic modulation recognition,” IEEE Network Letters, vol. 3, no. 2, pp. 47–51, 2021.
12. X. Zhang, Z. Luo, and W. Xiao, “CNN-BiLSTM-DNN-based modulation recognition algorithm at low SNR,” Applied Sciences, vol. 14, no. 13, 2024.
13. W. Kong, X. Jiao, Y. Xu, B. Zhang, and Q. Yang, “A transformer-based contrastive semi- supervised learning framework for automatic modulation recognition,” IEEE Transactions on Cognitive Communications and Networking, vol. 9, no. 4, pp. 950–962, 2023.
14. F. Zhang, C. Luo, J. Xu, Y. Luo, and F.-C. Zheng, “Deep learning based automatic modulation recognition: Models, datasets, and challenges,” Digital Signal Processing, vol. 129, art. no. 103650, 2022.
15. J. Xu, C. Luo, G. Parr, and Y. Luo, “A spatiotemporal multi-channel learning framework for automatic modulation recognition,” IEEE Wireless Communications Letters, vol. 9, no. 10, pp. 1629–1632, 2020.
16. B. Liu et al., “Deep hybrid transformer network for robust modulation classification in wireless communications,” Knowledge-Based Systems, vol. 300, art. no. 112191, 2024.
17. M. Shao, D. Li, S. Hong, J. Qi, and H. Sun, “IQFormer: A novel transformer-based model with multimodality fusion for automatic modulation recognition,” IEEE Transactions on Cognitive Communications and Networking, 2024.
18. T. J. O’Shea and N. West, “Radio machine learning dataset generation with GNU Radio,” Proc. GNU Radio Conference, vol. 1, no. 1, art. no. 1, 2016.
19. Y. Yu, X. Si, C. Hu, and J. Zhang, “A review of recurrent neural networks: LSTM cells and network architectures,” Neural Computation, vol. 31, no. 7, pp. 1235–1270, 2019.
20. S. Liu et al., “Convolutional neural network-based bidirectional gated recurrent unit– additive attention mechanism hybrid deep neural networks for short-term traffic flow prediction,” Sustainability, vol. 16, no. 5, 2024.
21. F. Zhang, C. Luo, J. Xu, and Y. Luo, “An efficient deep learning model for automatic modulation recognition based on parameter estimation and transformation,” IEEE Communications Letters, vol. 25, no. 10, pp. 3287–3290, 2021.