A Super Light Convolutional Neural Network for Automatic Modulation Recognition in Unmanned Aerial Vehicles based 6G Wireless Network

Debbarni Sarkar, *Student Member, IEEE,* Samarth Verma, Rupa Kumari, Yogita, *Senior Member, IEEE,* Vipin Pal, *Senior Member, IEEE,* and Satyendra Singh Yadav, *Senior Member, IEEE*

***Abstract*—Automatic Modulation Recognition (AMR) is a fundamental capability for Unmanned Aerial Vehicle (UAV) communication systems in sixth-generation (6G) wireless networks. It enables UAVs to intelligently identify and track received signals, supporting reliable connectivity under dynamic environments. In practical UAV applications, AMR methods must achieve high recognition accuracy with minimal computational complexity, since UAV platforms operate under strict constraints in storage, memory, and processing power. While recent Deep Learning (DL)-based solutions have advanced AMR performance, most prioritize accuracy at the cost of significantly larger models and higher computational demands. Conversely, lightweight models often lack the accuracy required for real-time deployment, limiting their practical utility. To overcome these limitations, this paper presents a novel Super Light Convolutional Neural Network (SLCNN) for AMR. Unlike conventional models, SLCNN employs a carefully optimized architecture with fewer convolutional layers, smaller filters, and pooling operations, combined with Gaussian noise and dropout for robust generalization. This design strategy reduces model size and inference time while preserving high accuracy. The proposed SLCNN was evaluated on the HisarMod 2019.1 dataset and validated across RML 2016.10a, 2016.10b, and 2018.01a datasets. Experimental comparisons with Convolutional Long Short-Term Memory Deep Neural Network (CLNN), Long Short-Term Memory, Gated Recurrent Unit, and Residual Network highlight that SLCNN achieves superior results, attaining 98.50% classification accuracy with significantly reduced computational cost. Furthermore, deployment on the NVIDIA Jetson Orin Nano demonstrates real-time suitability, confirming the model's effectiveness for UAV-based 6G wireless networks.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9500

***Index Terms*—Automatic Modulation Recognition, Unmanned Aerial Vehicles, Deep Learning, Super Light Convolution Neural Network, Feature Extraction, Computational Modeling.**

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D. Sarkar, S. Verma, R. Kumari, and Satyendra Singh Yadav are with the Department of ECE, National Institute of Technology Meghalaya, India (e-mails: p21ec004@nitm.ac.in, b20EC038@nitm.ac.in, b20EC040@nitm.ac.in, and satyendra@nitm.ac.in).

Yogita is with the Department of Computer Science and Engineering, National Institute of Technology Kurukshetra, India (e-mail: yogita@nitkkr.ac.in).

V. Pal is with the Department of Computer Science and Engineering, National Institute of Technology Delhi, India (e-mail: vipinpal@nitdelhi.ac.in).

I. Introduction

The primary objective of Sixth Generation (6G) wireless networks is to establish a robust and dependable connection among a vast number of devices while ensuring minimal latency and high data transmission rates. However, obtaining 6G capabilities remains a significant challenge due to rapidly expanding Internet of Things (IoT) applications and complex networks. These problems can be overcome by Unmanned Aerial Vehicles (UAVs), digitally coded programmable metasurface, intelligent reflecting surface, and other technologies [1]–[6]. UAV-based communication can improve network performance by quickly restoring services and reducing congestion in emergencies and densely populated locations. UAV-based communication uses drones as mobile base stations that can operate autonomously, flying freely or under the control of ground stations. These aerial base stations can be deployed flexibly to provide network coverage in high-demand areas or during emergencies. Therefore, the applications of UAVs are rapidly expanding across numerous sectors, impacting areas such as urban areas, rural areas, hill areas, and sea areas for military applications, traffic systems, medical, commercial, entertainment, communications, and construction [7], [8]. In many instances, leveraging UAVs for communication can prove more cost-effective than investing in conventional infrastructure.

On the other hand, Automatic Modulation Recognition (AMR) is vital in wireless communications [9], acting as an important bridge linking signal identification to interpretation. It aids in the recognition of modulation schemes employed in received signals. AMR is a vital component of intelligent receivers operating in non-cooperative environments, such as cognitive radio networks and military systems. It is employed in diverse applications, including interference detection, spectrum sensing, spectrum management, and electronic warfare. AMR is instrumental in analyzing radio frequency signals and is particularly crucial for advanced software-defined radios, especially in the aerospace domain. It improves spectrum efficiency, strengthens security, and decreases operational complexity [10]–[12]. AMR, powered by advanced artificial intelligence models. The Deep Learning (DL) model has established itself as a key player in AMR, excelling in seamlessly handling feature extraction and modulation classification tasks [13], [14]. It automatically extracts the most distinctive features from raw signal data and seamlessly adapts to different signal environments and modulation schemes.

AMR is also a key component in UAV-based communication [15]–[17] systems. It enables UAVs to detect modulation schemes automatically and reduce the impact of interference in a dynamic wireless environment. AMR empowers UAVs to operate independently in remote environments by eliminating the need for pre-configured communication settings, enhancing their adaptability and resilience. Recently, the rapid advancement of UAV communication techniques, along with the growing need for higher performance, has resulted in a wide range of modulation models and parameters being used in UAV communication systems. However, many parameters can degrade the performance of UAV-based communication systems. Therefore, a lightweight framework is an essential requirement for UAV-based 6G communication networks due to the restricted battery and power resources. A lightweight AMC algorithm is indispensable for extending UAV flight duration by optimizing power consumption, which maintains uninterrupted communication over extended periods. The state of the art work along with the research gaps identified filed are discussed in detail.

A. Related Work

This section offers a brief review of the current state-of-the-art research on AMR, examining significant studies and their contributions to the field. Conventional AMR techniques are broadly categorized into likelihood and feature-based methods [18]. Likelihood models are computationally intensive, requiring the estimation of unknown parameters within the classification model. They also struggle with channel coefficient estimates or timing offsets. In contrast, feature-based approaches depend on identifying unique signal features, which can be challenging and may limit their effectiveness in diverse environments. However, a single feature is often insufficient for accurately classifying signals within a large dataset. Various features have been investigated in AMR, comprising constellation shape metrics, higher-order statistics, wavelet transform features, and cyclic characteristics [19]. In [20], the authors review recent progress in applying deep neural networks to radio modulation recognition. The results indicate that performance is not constrained by network depth, suggesting that future research should focus on enhancing learned synchronization and equalization. A simplified Convolutional Neural Network (CNN) model was introduced to classify 10 distinct modulation formats effectively in [21]. In [22], the authors explore adapting CNNs to complex-valued radio signals for modulation classification. Compared to traditional expert feature methods, our approach learns features directly and shows notable performance gains, especially at low SNR. This demonstrates that blind temporal learning with deep CNNs is a strong, viable method for this task. A Convolutional Long-Short Term Deep Neural Network (CLDNN) was proposed in [20] by merging CNN and LSTM models within a deep neural network to leverage the complementary strengths of CNNs, LSTMs, and Deep Neural Networks (DNNs). Residual Networks (ResNets) [23] was developed to enhance feature propagation within neural networks significantly. An in-depth study compares DL and baseline methods for radio signal classification under various channel impairments [24]. Effects of carrier offset, symbol rate, and multipath fading are analyzed through simulations and lab measurements. Results highlight performance, training strategies, and key design considerations.

However, these complex models demand substantial computational resources, limiting their practicality in resource-constrained UAV applications. Therefore, researchers have proposed various lightweight AMR models [16], [25], [26] specifically focused on reducing computational complexity and parameter count. An innovative cooperative AMR was proposed in [16] by utilizing UAV-based communication. In [25], a novel AMR was designed for efficient computation and reduced model size. In [26], the proposed model effectively balances efficiency and accuracy on the RML2016.10a dataset. However, there has been limited research on AMC for resource-constrained UAV-based communications. The summary of the representative and their limitations are presented in Table I.

B. Contributions

In wireless communication, limited research has been conducted on AMC for resource-constrained UAV-based systems, especially considering the unique challenges these systems face, such as limited computational power, energy constraints, and dynamic environments. To address these challenges, it is essential to explore and develop a lightweight AMR model specifically tailored for UAV-based communication systems. The motivation behind this approach is to enhance the efficiency and reliability of UAV communications while minimizing resource consumption, enabling real-time processing, and ensuring smooth operation in resource-constrained environments. In this work, the aforementioned challenges of AMR in UAVs have been addressed by proposing a novel Super Light Convolutional Neural Network (SLCNN) model. The proposed SLCNN is designed to be computationally efficient while achieving robust modulation classification performance in the presence of realistic channel impairments. The model achieves high recognition accuracy with a significantly reduced number of parameters compared to conventional approaches. Additionally, the model's training and testing times outperform baseline models without compromising recognition accuracy, which makes the SLCNN suitable for different scenarios. The key contributions of this paper are listed as follows:

- A novel SLCNN model has been proposed for UAV-based communications. The SLCNN incorporates various layer types, employing convolutional layers for feature extraction. Further, dropout and Gaussian noise layers are utilized for regularization to mitigate overfitting during training.
- The proposed models have been thoroughly evaluated using the publicly available new HisarMod 2019.1 dataset. Further, the performance of the proposed SLCNN model has been evaluated and compared across different datasets, including RML 2016.10a, RML 2016.10b, RML 2018.01a, and HisarMod 2019.1.

TABLE I
SUMMARY OF REPRESENTATIVE AMR METHODS AND THEIR LIMITATIONS

Reference	Method / Model	Key Contribution	Limitations or Advantages for UAV AMR
[18]	Likelihood and Feature-based	Early categorization; likelihood needs parameter estimation; feature-based relies on manual feature extraction.	High computational cost; sensitive to channel estimation errors; limited robustness in dynamic UAV scenarios.
[19]	Feature-based AMR	Investigated various features: constellation metrics, higher-order stats, wavelets, cyclic features.	Single features insufficient; hand-crafted features may not generalize well.
[22]	CNN2, CNN3, DNN (RML2016.10a)	Introduced deep CNNs for raw IQ signal classification; demonstrated learned feature extraction; popular benchmark dataset.	Good accuracy but increased model size; lacks real-time testing optimization for UAVs.
[21]	Simplified CNN	Efficient CNN for classifying 10 modulations with improved low-SNR performance.	Still moderate computational demand; less suitable for tight UAV latency constraints.
[20]	CLDNN	Combined spatial and temporal learning; leveraged strengths of CNNs and RNNs.	High complexity; unsuitable for embedded UAV processors.
[23]	ResNet	Enhanced feature propagation through residual connections; improved deeper models.	Large parameter count; high training and testing cost.
[24]	DL vs. Baseline Methods	Compared DL and traditional methods under channel impairments (e.g., fading, carrier offset).	No focus on lightweight deployment or embedded optimizations.
[25]	LightAMC	Proposed lightweight AMR with reduced complexity and model size.	Promising for UAVs; but further real-time tests needed.
[16]	Cooperative AMR	Proposed cooperative AMR with UAV communications to improve recognition	Innovative but requires reliable coordination between nodes
[26]	Lightweight AMR	Balanced model efficiency and accuracy on RML2016.10a.	Limited exploration of pruning/quantization; more field testing needed for UAV scenarios.
This work	Proposed SLCNN (HisarMod 2019.1)	Lightweight SLCNN designed for UAV AMR; integrates Gaussian noise, dropout, and fewer filters for efficient generalization; validated on HisarMod 2019.1 dataset.	Specifically optimized for resource-constrained UAVs; achieves robust classification with low testing time; practical for dynamic conditions.

- The accuracy, precision, recall, and F1-score of the proposed model have been compared with four baseline models, such as CLDNN, GRU, LSTM, and ResNet. Additionally, the performance of the proposed model has been evaluated across various parameters, including different learning rates and dropout rates. Furthermore, a comparison of training and testing time complexity has been conducted among the models.
- The proposed SLCNN model's ability to classify all 26 modulation schemes has been extensively analyzed and presented. Moreover, the proposed model's confusion matrices have been presented at various SNR levels to demonstrate its efficacy.
- The experiment has been further evaluated on the Jetson Orin Nano, thereby substantiating its suitability for embedded hardware deployment within the system under consideration.

The remainder of the paper is organized as follows: section II outlines the system model and problem formulation. Section III provides a detailed explanation of the proposed SLCNN model. Section IV covers the experimental setup and relevant background information. Section V analyzes the results and their implications. Finally, section VI concludes the work.

II. SYSTEM MODEL AND PROBLEM FORMULATION

This section presents the system architecture for AMR-based UAV communication and formally defines the problem to be addressed.

A. System Model

The AMR-based UAV communication system model is considered as depicted in Fig. 1. In this context, the UAV traverses various regions, including urban, coastal, rural, and upland areas, while AMR is conducted on the receiver side for signal identification. The transmitter modulates the input signals into radio frequency signals. These signals then propagate through a channel before being received by the receiver. Upon reception, the receiver converts the signals into a baseband complex signal sequence denoted by $X = \{x(0), x(1), ..., x(K-1)\}$, where K represents the number of sampling points. This preprocessing step prepares the signal for subsequent analysis. The final stage involves identifying the modulation type by comparing it to a predefined set of possible modulation schemes, represented by $Y = \{y_i, i = 1, 2, ..., N\}$, where N signifies the total number of modulation types and y_i denotes each specific type. The received signal can be generally represented as

$$x(k) = h(k) \times s(k) + n(k), \qquad k \in [1, \cdots, K] \tag{1}$$

where $x(k)$ denotes the received signal by the UAV, which is commonly recorded in and quadrature phase format. $s(k)$ represents the transmitted signal, $n(k)$ denotes the additive white Gaussian noise with zero mean and variance σ^2, and $h(k)$ denotes the wireless channel. The IQ format is mathematically expressed as $I = A_m cos(\phi)$ and $Q = A_m sin(\phi)$,

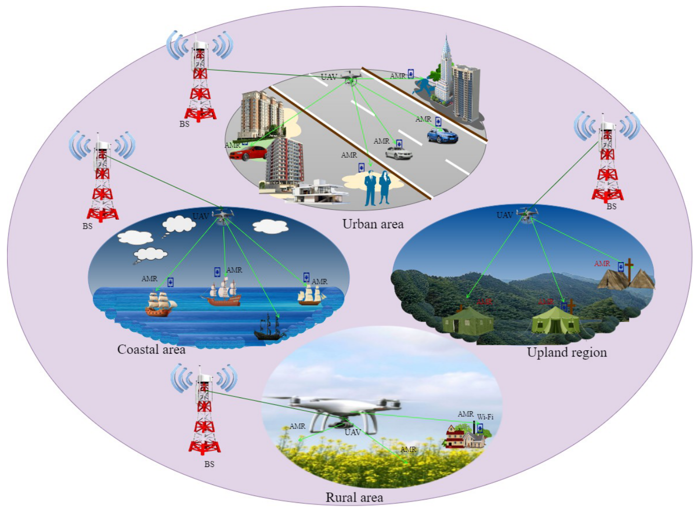


Fig. 1. System model of AMR-based UAV communication.

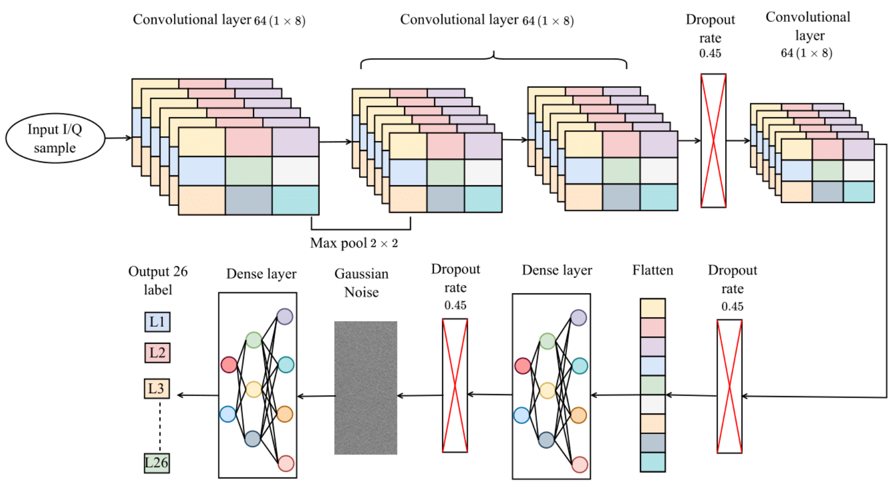


Fig. 2. Structure of the proposed SLCNN architecture.

where A_m signifies the instantaneous amplitude of the received signal $x(k)$, and ϕ represents its instantaneous phase.

B. Problem Statement

In the DL-based AMR problem, a modulation classifier strives to determine the posterior probability, denoted by $P(s(k) \in N_i|x(k))$, that the transmitted signal $s(k)$ belongs to class N_i. This determination is based solely on the received signal $x(k)$. This paper aims to develop a neural network model that achieves high AMR accuracy while maintaining low computational complexity. Therefore, a novel SLCNN model has been proposed. This SLCNN model aims to balance model size, computational efficiency, and classification accuracy by achieving a lightweight structure, minimal memory footprint, and low computational cost.

III. Proposed DL Model

The datasets were imported into Jupyter Notebook for simulation. The simulations were conducted on a computing system equipped with an Intel® Xeon® W-2104 Central Processing Unit (CPU) operating at 3.20 Gigahertz (GHz), 32 Gigabytes (GB) of Random Access Memory, and 2 NVIDIA Quadro RTX 5000 Graphics Processing Units (GPUs), each possessing 6 GB of memory. Fig. 2 illustrates the architecture of the proposed SLCNN model, which includes 12 neural network layers. The model integrates several regularization techniques, specifically Gaussian noise, Dense, and Dropout layers, to enhance generalization and reduce overfitting. The Gaussian noise layer adds random noise sampled from a normal distribution to the input data during training, helping the model become more resilient to signal variations, interference, and channel distortions common in UAV communications. Dropout layers strengthen this by randomly deactivating a fraction of neurons at each training step, forcing the network to rely on multiple redundant pathways for feature extraction. This prevents the network from memorizing noise or outliers. Dense layers connect all neurons in one layer to the next, enabling the network to capture complex relationships and subtle patterns in the modulated IQ signals. For UAV applications, minimizing execution time while maintaining high accuracy is critical, so the proposed model uses fewer filters per layer to reduce computational complexity. Together, these design choices allow the SLCNN to deliver high classification accuracy, robust performance on unseen or noisy data, and efficient execution. Additionally, a comprehensive hyperparameter tuning process is conducted to optimize performance by carefully adjusting learning rate, dropout rate, filter sizes, number of filters, and network depth. This is crucial because these parameters directly affect the model's ability to extract meaningful features without overfitting or underfitting. Exploring different combinations of convolutional layer sequences and filter counts helps identify the best architecture for balancing accuracy and efficiency. Such tuning ensures the model captures relevant signal patterns effectively, stays robust against real-world noise and channel variations, and performs reliably for real-time UAV signal classification.

The system receives modulated signals represented as 2×1024 IQ time-domain vectors, which are reshaped and zero-padded before being fed into the first convolutional layer. The model employs four two-dimensional convolutional layers to extract meaningful features. The first two layers use 32 filters each, with kernel sizes of 1×8 and 1×4 to first capture broad, generic signal patterns and then refine local details. The next two layers increase to 64 filters with a 1×8 kernel to learn more complex, higher-level features while maintaining sufficient time-domain coverage. It is followed by a Rectified Linear Unit (ReLU) activation for output normalization. The choice of kernel size significantly impacts performance because it defines how much of the input signal is processed at once. Larger kernels capture long-term dependencies but may miss subtle local variations, while smaller kernels extract fine details but can limit the model's ability to learn broader patterns if too small. Likewise, filter size influences the network's capacity to learn diverse features: more filters help detect a wide range of patterns but add computational cost and potential overfitting; fewer filters reduce complexity but may limit feature richness. Therefore, the proposed combination of kernel sizes and filter counts is designed to balance local detail and global pattern extraction, ensuring accurate, robust performance while keeping computational demands manageable. This balance is crucial for real-time UAV communications, where the system must classify signals reliably and efficiently under dynamic and noisy conditions. By combining multiple kernel sizes and filter configurations in a progressive structure, the model effectively learns relevant signal characteristics without unnecessary overhead, making it well-suited for practical deployment. The ReLU is used because it adds non-linearity, avoids the vanishing gradient problem, and speeds up training, helping the model learn complex patterns efficiently. Further, max pooling is employed after the first convolutional layer to reduce the dimensionality of the data and keep important features, thereby lowering computational complexity and mitigating overfitting to some extent, which helps prevent overfitting for efficient and robust performance.

Dropout layers are added after the third and fourth convolutional layers and the first dense layer to improve generalization. They randomly deactivate neurons during training, which prevents the network from relying too heavily on specific features and helps reduce overfitting. This encourages the model to learn multiple redundant features, making it more robust to noise and variations. A Gaussian noise layer before the final output further regularizes the model by adding random noise during training, helping it handle real-world signal distortions. This reduces sensitivity to small input changes and improves generalization to new, unseen UAV communication signals. A flatten layer converts the 2D feature maps into a 1D vector, preparing the data for the dense layers. This allows the model to combine all extracted features into a single representation. Finally, the last dense layer uses a softmax activation function to produce a probability distribution over the signal classes, enabling confident and accurate UAV signal classification even in dynamic conditions. The equation for the softmax function is shown as follows:

$$softmax\left(y_j\right) = \frac{e^{y_j}}{\sum_{k=1}^{K} e^{y_k}} \quad for\ j = 1, \ldots, N \tag{2}$$

Following its passage through the aforementioned layers, the system classifies the input signal by assigning it to the most probable class. Table II details the specific layers and parameters used to construct the SLCNN model.

TABLE II
THE SLCNN MODEL'S SETUP

Layer (type)	Output Shape	Description
Input	2, 1024, 1	Input: 2x1024 IQ vectors
Conv2D	2, 1024, 32	Number of filters: 32; Kernel size: (1,8); Stride: (1,1); Activation: ReLU
MaxPooling2D	1, 512, 32	Pool size: (2,2)
Conv2D	1, 512, 32	Number of filters: 32; Kernel size: (1,4); Stride: (1,1); Activation: ReLU
Conv2D	1, 512, 64	Number of filters: 64; Kernel size: (1,8); Stride: (1,1); Activation: ReLU
Dropout	1, 512, 64	Dropout rate: 0.45
Conv2D	1, 512, 64	Number of filters: 64; Kernel size: (1,8); Stride: (1,1); Activation: ReLU
Dropout	1, 512, 64	Dropout rate: 0.45
Flatten	32,768	Flattens multi-dimensional input
Dense	64	Activation: ReLU
Dropout	64	Dropout rate: 0.45
GaussianNoise	64	Standard deviation: 1
Dense (Output)	26	Fully connected layer; Activation: Softmax

IV. Experimental Background

A. Dataset

So far, most AMR studies have focused on publicly available datasets such as RML 2016.10a [20], [21], [26], RML 2016.10b [27], and RML 2018.01a [28]. However, research using the publicly available HisarMod 2019.1 dataset [28] has been limited. Therefore, this paper utilizes the HisarMod 2019.1 dataset to evaluate the performance of the proposed SLCNN model. This dataset provides a comprehensive collection of signals with 26 modulation types such as binary phase-shift keying (BPSK), quadrature phase-shift keying (QPSK), 8-phase-shift Keying (8PSK), 16PSK, 32PSK, 64PSK, 4-quadrature amplitude modulation (4QAM), 8QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, 2-frequency shift keying (2FSK), 4FSK, 8FSK, 16FSK, 4-pulse amplitude

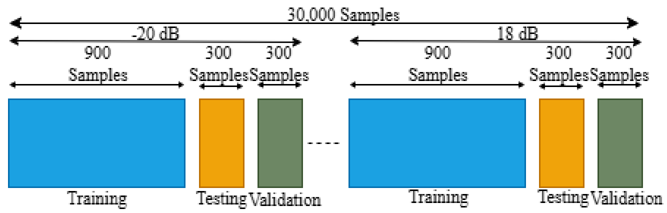


Fig. 3. Training, testing, and validation data samples for each modulation scheme.

modulation (4PAM), 8PAM, 16PAM, amplitude modulation-double sideband (AM-DSB), AM-DSB-suppressed carrier (AM-DSM-SC), AM-upper side band (AM-USB), AM-lower side band (AM-LSB), frequency modulation (FM) and phase modulation (PM). It also models several channels, including ideal, static, Rayleigh fading, Rician fading (with $K = 3$), and Nakagami-m fading (with $m = 2$). The ideal channel indicates no fading with only additive white Gaussian noise. In the static channel, coefficients are randomly set once and remain constant. Rayleigh fading models non-line-of-sight conditions, while Rician fading represents mild fading. Further, Nakagami–m fading is used to model the received power distribution, which indicates that the dataset includes signals under various fading models. The dataset includes 780,000 I/Q signal samples, each of length 1024, labeled by modulation type and SNR level. It reflects realistic channel conditions by incorporating effects like sample rate offset, frequency offset, multipath fading, and thermal noise, with SNR levels ranging from -20 dB to +18 dB in 2 dB steps.

B. Implementation Details

The training and testing procedures are executed using the Keras DL API, with TensorFlow as the computational backend and an Nvidia M60 GPU for acceleration. The dataset consists of 26 modulation types and 20 SNR levels. Therefore, total combinations = 26 modulation types $\times$ 20 SNR levels = 520 combinations. 7,80,000 samples equally split among 520 combinations. As a result, $\frac{7{,}80{,}000}{520} = 1{,}500$. Each unique modulation SNR pair contains 1,500 samples, which are then divided into 60% training, 20% validation, and 20% testing subsets (i.e., 900, 300, and 300 samples, respectively), as shown in Fig. 3. Accordingly, for each modulation type, the total number of samples is given by $1{,}500 \times 20$ (SNR levels), yielding 30,000 samples. In this study, the dataset is explicitly constructed to be balanced, each modulation SNR pair contains the same number of samples (1,500), ensuring uniform representation across all classes and SNR levels. Consequently, there is no inherent class imbalance in the training, validation, or test sets. As a result, the model does not require additional techniques such as class weighting in the loss function or data augmentation to correct for imbalance. The balanced design helps the model learn each class equally well without biasing predictions toward any particular modulation type or SNR range. When class imbalance is present, various strategies can be used to prevent the model from being biased toward the majority classes. Weighted loss functions adjust the training loss so that errors on minority classes are penalized more heavily, encouraging the model to learn rare classes more effectively. Oversampling minority classes balances the dataset by duplicating existing samples or generating synthetic examples, ensuring that underrepresented classes appear more frequently during training. Data augmentation techniques further help by creating new, varied samples for minority classes through transformations such as adding noise, shifting signals, or applying small distortions, which improves the model's generalization. Together, these methods help maintain balanced performance across all classes, even when the original dataset is biased.

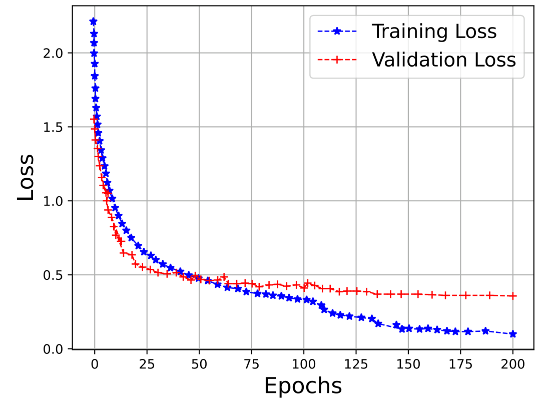


Fig. 4. Training process of the proposed model at learning rate = 0.001 and dropout rate = 0.45.

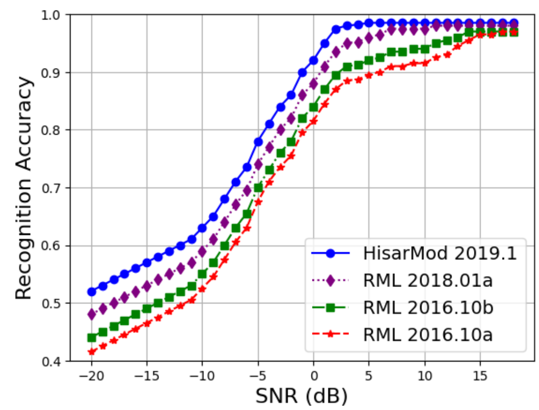
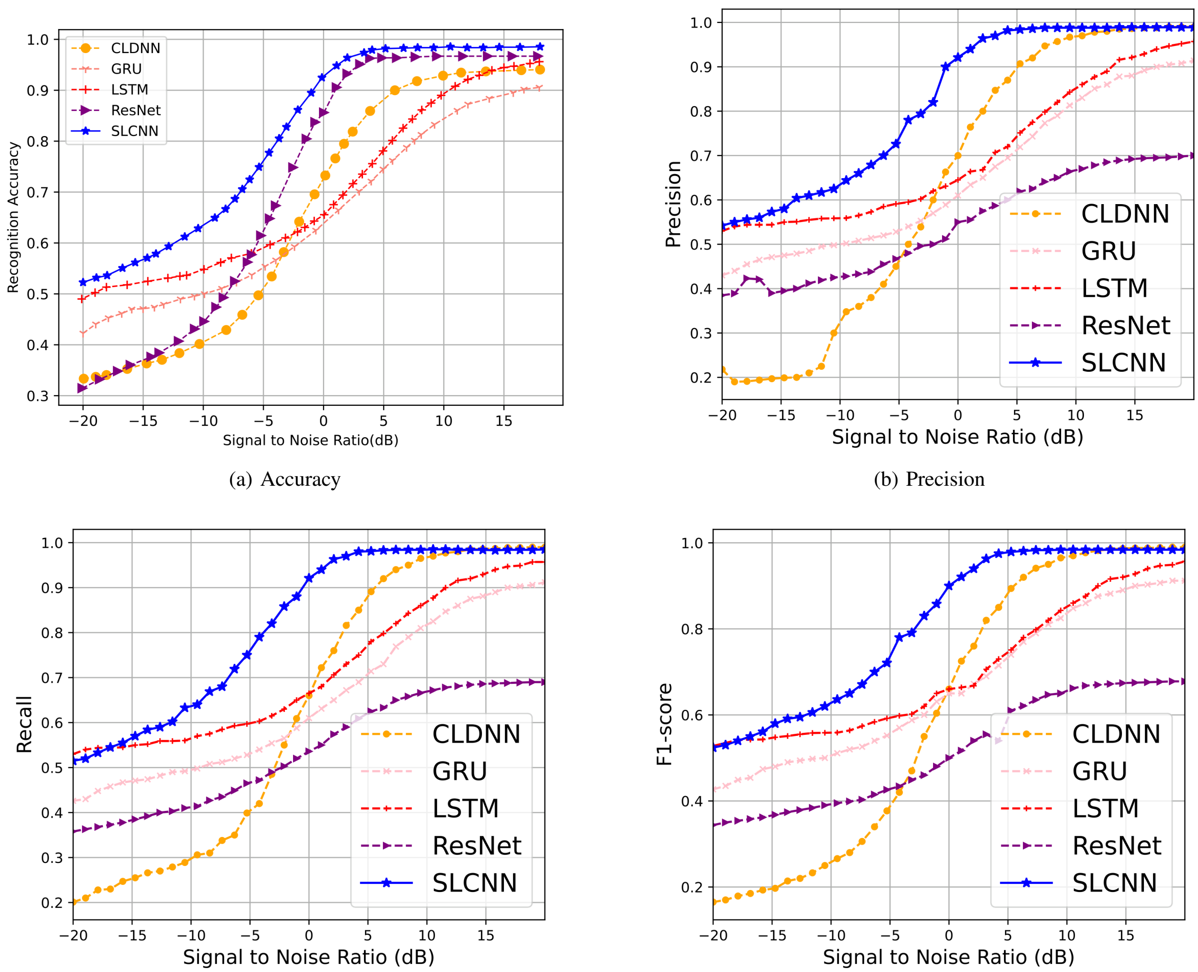


Fig. 5. Comparison of the proposed model performance on different datasets.

A callback function monitors validation loss during training, and if the validation loss does not show improvement for a designated number of epochs (with a patience of 5 epochs), the learning rate is reduced by half. If no further progress is observed over a longer duration (with patience of 40 epochs), training is terminated early, and the model with the lowest validation loss is preserved. The SLCNN model is trained from scratch, initializing all weight parameters randomly and running for 200 epochs to ensure adequate convergence. The training process involves tuning various hyperparameters, including learning rate and batch size, to identify the optimal settings for maximizing model performance. The Adam



(a) Accuracy (b) Precision

(c) Recall (d) F1-score

Fig. 6. Performance comparison between the baseline and proposed models: (a) Accuracy, (b) Precision, (c) Recall, and (d) F1-score, at a learning rate of 0.001 and a dropout rate of 0.45.

optimizer is employed for efficient gradient descent, and the categorical cross-entropy loss function is used to assess the difference between predicted and actual class labels.

V. Simulation Results Analysis and Discussions

This section examines the system's performance by evaluating the accuracy rate, computational time, and the effects of different simulation parameters. For the system under consideration, the bandwidth and carrier frequency are taken as 20 Megahertz (MHz) and 2.4 GHz, respectively [29]. In the context of 6G UAV deployments, UAV speeds may range from 60 km/h to 480 km/h, as reported in [29], [30]. Consequently, the corresponding Doppler shifts fall within 133 Hz to 1067 Hz, which are negligible when compared to the system bandwidth of 20 MHz [29]. Therefore, it can be concluded that the Doppler effect exerts an almost insignificant influence on the system's performance across both low and high-speed UAV scenarios. All models have been implemented and tested using the same GPU and the HisarMod 2019.1 dataset. During the simulation, it was observed that both the baseline and proposed models performed optimally, utilizing a 0.001 learning rate and a 0.45 dropout rate. Consequently, these parameters have been set for the upcoming simulation.

A. Training and Validation Performance

Fig. 4 shows the training and validation loss curves of the proposed SLCNN model over 200 epochs, with a learning rate of 0.001 and a dropout rate of 0.45. Both losses demonstrate good convergence, with the model reaching a minimum loss value of 0.48, indicating effective learning and strong generalization. Notably, the model begins training with a relatively low validation error and maintains this advantage throughout, showing its ability to avoid overfitting. Since lower loss directly relates to higher classification accuracy, this result implies reliable signal recognition performance. In practical UAV applications, such convergence behaviour suggests that the SLCNN model could run efficiently on onboard hardware with limited computational resources, potentially lowering power consumption and extending flight time.

B. Performance Comparison to other Datasets

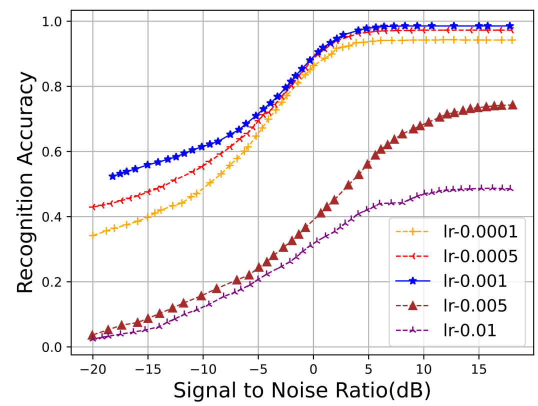
Fig. 5 presents the accuracy comparison of the proposed SLCNN model evaluated over 200 epochs using different datasets, including RML 2016.10a, RML 2016.10b, RML 2018.01a, and HisarMod 2019.1. The model is trained with a learning rate of 0.001 and a dropout rate of 0.45. The comparison indicates that the SLCNN model trained on the HisarMod 2019.1 dataset consistently achieves higher recognition accuracy across the entire SNR range compared to the results from the RML 2018.01a, RML 2016.10b, and RML 2016.10a datasets. Notably, the HisarMod 2019.1 curve shows a more rapid improvement in accuracy at low SNR levels (below 0 dB), demonstrating greater robustness under noisy channel conditions. The proposed model attains high accuracy values as the SNR increases for different datasets. These results suggest that the proposed SLCNN model contributes to more reliable and resilient modulation recognition.

C. Performance Comparison

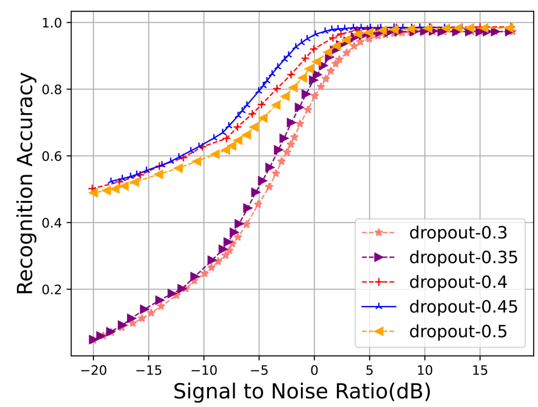
A comprehensive performance evaluation has been presented in Fig. 6 to compare the proposed SLCNN model with four baseline models: CLDNN, GRU, LSTM, and ResNet, using a learning rate of 0.001 and a 0.45 dropout rate. In Fig. 6(a), the SLCNN achieves an overall recognition accuracy of 98.5%, outperforming ResNet (97.8%), CLDNN (93.9%), LSTM (94.2%), and GRU (90.3%). In terms of precision (Fig. 6(b)), SLCNN also leads with 83%, compared to ResNet (54.2%), CLDNN (63.8%), LSTM (70.2%), and GRU (65.2%). Similarly, for recall (Fig. 6(c)), the SLCNN achieves 81.19%, which is significantly higher than ResNet (54.09%), CLDNN (62.97%), LSTM (71.35%), and GRU (64.91%). The F1-score (Fig. 6(d)) further confirms this trend, with SLCNN scoring 81.49% compared to ResNet (52.48%), CLDNN (61.41%), LSTM (70.3%), and GRU (66.52%). These results demonstrate that the proposed SLCNN consistently outperforms the baselines across all key metrics, achieving robust performance under both low and high SNR conditions. This superior performance has important implications for UAV applications: its higher precision and recall mean more reliable signal classification even in noisy or fast-changing environments, such as those affected by Doppler shifts due to UAV mobility. Additionally, the SLCNN's streamlined architecture and fewer filters help reduce computational load, which can lead to lower onboard power consumption, a critical factor for battery-constrained UAVs.

D. Effect of Varying Learning Rate and Dropout Rate

A hyperparameter tuning exercise was conducted to evaluate the SLCNN model's performance under different learning and dropout rates. Fig. 7(a) shows the effect of varying the learning rate (0.01, 0.005, 0.001, 0.0005, and 0.0001) with a fixed dropout rate of 0.45. It was observed that gradually reducing the learning rate initially improved the model's performance by allowing more stable and precise weight updates. However, if the learning rate was too low, the model's performance degraded due to slow convergence and possible entrapment in local minima. The SLCNN achieved its best classification accuracy at a learning rate of 0.001, maintaining robust performance even under low SNR conditions, which is essential for reliable UAV signal recognition in noisy environments. Similarly, Fig. 7(b) illustrates the impact of varying dropout rates (0.3 to 0.5) with a fixed learning rate of 0.001. As the dropout rate increased, the model's generalization improved because higher dropout forces the network to learn redundant, robust features. However, excessively high dropout (beyond 0.45) weakened performance, likely due to too much information being randomly discarded during training. The optimal balance was found at a 0.45 dropout rate, which effectively reduced overfitting while preserving the network's learning capacity. These findings have practical implications for UAVs, as selecting appropriate hyperparameters like learning rate and dropout rate helps keep the model lightweight, accurate, and energy-efficient, all crucial for limited onboard hardware. A well-tuned model reduces computational workload and power consumption, extending UAV battery life. Better generalization also enables the SLCNN to handle challenges like signal fluctuations, interference, and Doppler shifts from UAV motion, ensuring stable communication links in dynamic conditions.

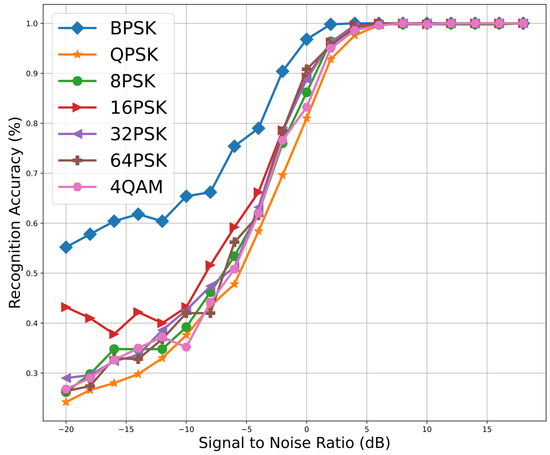


(a) Impact of Learning Rate

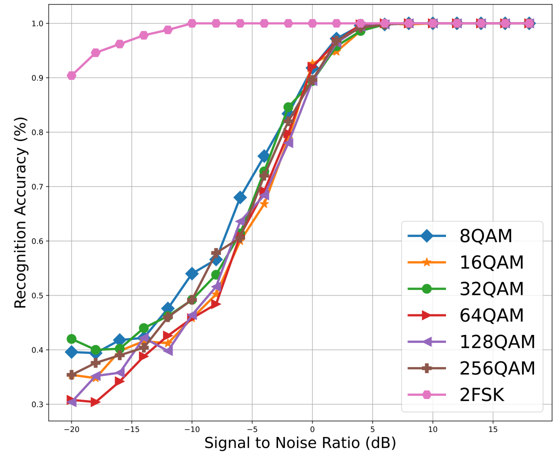


(b) Impact of dropout rate at learning rate = 0.001

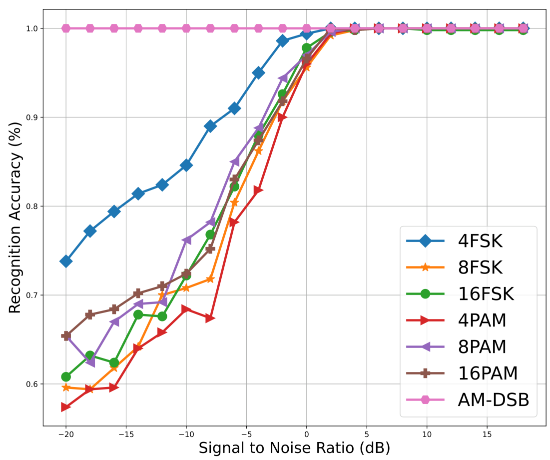
Fig. 7. Classification performance with varying simulation parameters: (a) Learning rate at dropout 0.45, (b) Dropout at learning rate 0.001.



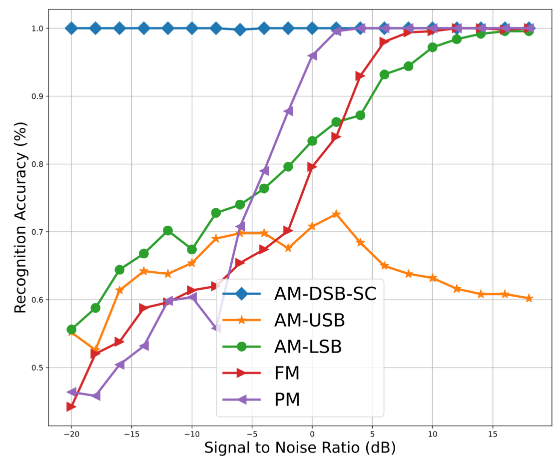
(a) BPSK, QPSK, 8PSK, 16PSK, 32PSK, 64PSK, and 4QAM



(b) 8QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, and 2FSK



(c) 4FSK, 8FSK, 16FSK, 4PAM, 8PAM, 16PAM, and AM-DSB



(d) AM-DSM-SC, AM-USB, AM-LSB, FM, and PM

Fig. 8. Performance of the SLCNN model on 26 modulation schemes from HisarMod 2019.1: (a) BPSK, QPSK, 8PSK, 16PSK, 32PSK, 64PSK, and 4QAM; (b) 8QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, and 2FSK; (c) 4FSK, 8FSK, 16FSK, 4PAM, 8PAM, 16PAM, and AM-DSB; (d) AM-DSM-SC, AM-USB, AM-LSB, FM, and PM.

E. Classification Performance and Convergence

Fig. 8 comprehensively depicts the classification performance of the proposed SLCNN model for all 26 modulation schemes. Fig. 8(a) shows that for the proposed model, BPSK modulation performs best among QPSK, 8PSK, 16PSK, 32PSK, 64PSK, and 4QAM. It has also been presented that after 5 dB SNR, the accuracy of these modulations is 100%. Further, Fig. 8(b) presents that the performance of 2FSK modulation is best among 8QAM, 16QAM, 32QAM, 64QAM, 128QAM, and 256QAM modulation scheme. Here, also after 5 dB SNR, the accuracy of these modulations is 100%. From Fig. 8(c) and 8(d), it has been seen that the performance of the AM-DSB and AM-DSM-SC modulations is the same, and these modulations' algorithms are superior to 4FSK, 8FSK, 16FSK, 4PAM, 8PAM, 16PAM, AM-USB, AM-LSB, FM, and PM. At high SNR, the classification accuracy for AM-USB modulation decreases because AM-USB and AM-LSB exhibit highly similar spectral characteristics, differing only in the orientation of the transmitted sideband. Both modulation schemes utilize the same carrier frequency and suppress one sideband while transmitting information on the other, resulting in mirror-symmetric spectra about the carrier frequency. In low-SNR scenarios, noise and channel distortions can introduce asymmetries that a classifier can exploit; however, as the SNR increases and the signal becomes cleaner, these distortions diminish, leaving only the inherent spectral features. If the feature extraction or classification model does not adequately capture phase information or spectral asymmetry, it may fail to distinguish between these mirror-image spectra, leading to increased misclassification at high SNR [31]. Nevertheless, the proposed model still shows strong overall AMR classification performance across all modulation types. The proposed SLCNN achieves high AMR accuracy, saving power and supporting longer UAV missions. Its lightweight design suits limited onboard hardware and adapts well to Doppler shifts and channel changes, ensuring reliable and efficient UAV communication.

TABLE III
COMPARISON OF COMPUTATIONAL TIME

Models	Training time (s/epoch)	testing time (s/sample)
CLDNN	341	210
GRU	177	151
LSTM	220	189
ResNet	492	393
SLCNN	**87**	**49**

TABLE IV
TESTING TIME COMPARISON ON JETSON ORIN NANO

Model	Quantization	Throughput (QPS)	Mean latency (ms)	GPU Compute (ms)
CLDNN	IN8	786.72	1.292	1.266
	FP16	786.72	1.292	1.266
	TF32	755.11	1.348	1.319
SLCNN	IN8	**2124.70**	**0.490**	**0.466**
	FP16	1907.07	0.546	0.520
	TF32	1305.69	0.793	0.761

F. Confusion Matrix Analysis

Fig. 9 presents the confusion matrices for the proposed SLCNN model at SNR values of -6 dB, -2 dB, 4 dB, and 10 dB. From Fig. 9(a), it has been seen that the performance of 2FSK, 4FSK, 16PAM, AM-DSB, and AM-DSB-SC modulations is 85% or more than 85% at -6 dB SNR, and among these modulations, the performance of 2FSK, AM-DSB, and AM-DSB-SC modulations is 100%. However, at this SNR, the QPSK and 32PSK modulations' performance is 55%, which is lower than the other modulations. In Fig. 9(b), the performance of BPSK, 32QAM, 2FSK, 4FSK, 8FSK, 16FSK, 4PAM, 8PAM, 16PAM, AM-DSB, AM-DSB-SC, AM-USB and PM are 85% or more than 85% at -2 dB SNR. At this SNR, 2FSK, AM-DSB, and AM-DSB-SC exhibit perfect performance with 100%, and AM-LSB has the lowest performance with 66%. Fig. 9(c) shows that the performance of all modulations except AM-LSB is 90% or above at 4 dB SNR, where BPSK, 8PSK, 32PSK, 64PSK, 4QAM, 8QAM, 128QAM, 256QAM, 2FSK, 4FSK, 8FSK, 16FSK, 4PAM, 8PAM, 16PAM, AM-DSB and AM-DSB-SC achieves 100% performance. However, at this SNR, AM-LSB performance has not improved beyond -2 dB SNR. In Fig. 9(d), at 10 dB SNR, the performance of all modulations is 100% except AM-USB and AM-LSB. The performance of AM-USB and AM-LSB modulations is 91% and 71%, respectively. Consequently, the results indicate that the SLCNN model exhibits markedly improved performance across all modulation types, with rising performance levels as the SNR increases.

G. Complexity Analysis

Time complexity signifies the duration required for the network to classify a single signal. Table III summarizes the training and testing time (prediction time) for all baseline models and the proposed SLCNN model. In Table III, the training time of CLDNN, GRU, LSTM, ResNet, and SLCNN is 341 sec (s), 177s, 220s, 492s, and 87s, respectively. Conversely, for CLDNN, GRU, LSTM, ResNet, and SLCNN's training time is 210s, 151s, 189s, 393s, and 49s, respectively. Faster training and testing time reduces power use and workload, extends UAV battery life, and helps handle Doppler shifts, making the SLCNN efficient and reliable for real-time UAV use.

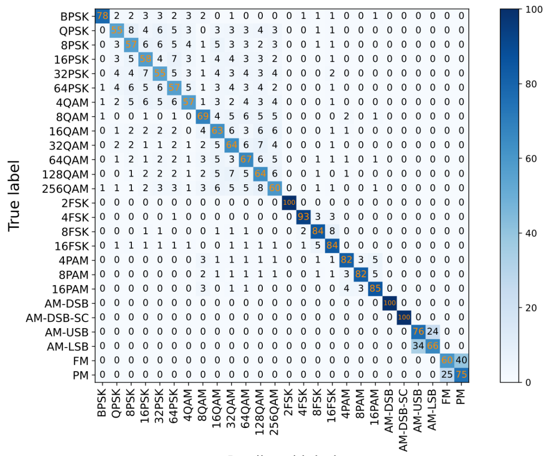
H. Comparative Testing Time Analysis on Jetson Orin Nano

To assess the performance of the proposed model on real-time hardware, evaluations have been conducted using the NVIDIA Jetson Orin Nano development platform, equipped with 8 GB of RAM. The device integrates the NVIDIA Ampere Graphics Processing Unit with 1024 Compute Unified Device Architecture cores, delivering up to 40 Tera Operations Per Second of artificial intelligence performance, supported by 8 GB of 128-bit Low-Power Double Data Rate 5 memory with 68 GB per second bandwidth. It is further equipped with a 6-core Arm Cortex-A78AE CPU and 2 NVIDIA DL Accelerator version 2.0 units, while offering support for 1080p30 video encoding and decoding. With a compact form factor of 70 millimeters by 45 millimeters and a configurable power consumption range of 7 to 15 Watts. For hardware-based evaluation, the CLDNN baseline, which exhibits the second-highest training and testing time among the four baseline models, has been considered for comparison with the proposed model. FP16, INT8, and TF32 are numerical precision formats used in computing for training and testing time. Table IV presents the throughput in Queries per Second (QPS), mean latency (ms), and GPU computation time (ms) for the SLCNN and CLDNN models. It has been observed that, across all techniques, the proposed SLCNN model achieves 170.1% higher throughput than the CLDNN model by IN8. Moreover, the SLCNN model exhibits lower mean latency and reduced GPU computation time, indicating improved efficiency over the CLDNN model. The SLCNN model exhibits a maximum latency and GPU time of 0.793 and 0.761 ms, respectively, whereas the CLDNN model demonstrates a latency and GPU time of 1.348 and 1.319 ms, respectively, using TF32.

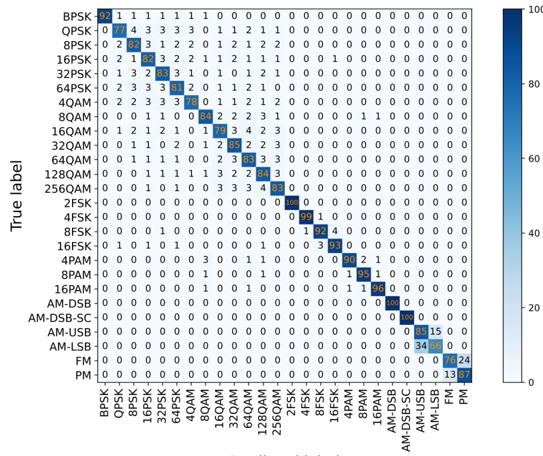
The proposed SLCNN model demonstrates low complexity and high efficiency due to fewer convolutions and trainable parameters, achieving an 8 times speedup over ResNet. While LSTM and GRU models incur longer testing times or reduced accuracy. Moreover, the hardware evaluation shows that the SLCNN model is almost 1.7 times faster than the CLDNN model in latency and exhibits a comparable improvement in GPU computation time. Therefore, SLCNN offers a favorable balance, making it well-suited for UAVs and other resource-constrained devices.

VI. CONCLUSION

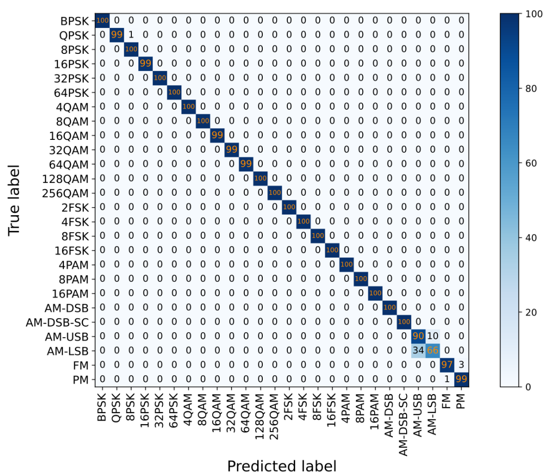
In this paper, an innovative DL model was presented for AMR in UAV communication systems. The model was designed to prioritize high classification accuracy across various SNR regimes while maintaining low computational complexity. This accuracy was achieved with a reduced filter count, resulting in faster execution times. Additionally, the integration of Gaussian noise effectively mitigated overfitting. Simulations demonstrated that the proposed model surpassed baseline model schemes across various SNRs. These findings confirmed



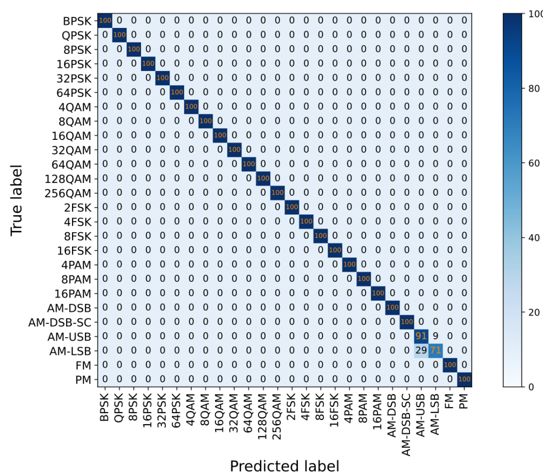
(a) -6 dB SNR



(b) -2 dB SNR



(c) 4 dB SNR



(d) 10 dB SNR

Fig. 9. Classification performance at different SNR levels: (a) -6 dB, (b) -2 dB, (c) 4 dB, and (d) 10 dB.

the efficiency of the SLCNN model and its suitability for deployment in edge environments with limited computational resources. This focus on efficiency makes the model especially well-suited for instantaneous and latency-sensitive scenarios in UAV networks. Hence, the proposed AMR model offers promising applications in 6G UAV-assisted communication systems. Although the HisarMod 2019.1 dataset serves as a valuable benchmark with diverse fading environments and 26 modulation types, it does not fully capture non-Gaussian motor interference. Future work might be focused on developing adaptive strategies to mitigate such impairment. Moreover, along with the practical considerations already addressed, future work might involve a comparative study without the Gaussian noise layer or with different kernel sizes.

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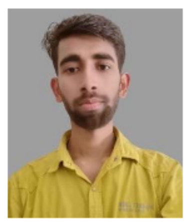
Debbarni Sarkar (Student Member, IEEE) received her Ph.D. degree in 2025 from the National Institute of Technology Meghalaya, India. Her research interests include intelligent Reflecting Surfaces, Non-orthogonal multiple access (NOMA), Internet of things (IoT), Hybrid automatic repeat request (HARQ), and machine learning (ML) and deep learning (DL) applications for wireless communication. She is a reviewer for various IEEE, Elsevier, Springer, Transactions/Journals, and conferences.



Samarth Verma received his Bachelor of Technology degree in Electronics and Communication Engineering from the National Institute of Technology Meghalaya, a prestigious institution designated as an institute of national importance, in 2024. During his studies, he cultivated deep expertise in various domains of electronics and communication, with a particular emphasis on cutting-edge advancements in wireless communication and networking. His primary research interests are wireless communication systems, Internet of Things (IoT) networks, and the integration of Artificial Intelligence (AI) and Machine Learning (ML) in these fields.

Rupa Kumari received her Bachelor of Technology degree in Electronics and Communication Engineering from the National Institute of Technology Meghalaya, a premier institution recognized as an institute of national importance, in 2024. Throughout her academic journey, she has developed a profound expertise in various aspects of electronics and communication, with a specific focus on emerging technologies in wireless communication and networking. Her primary research interests are wireless communication systems, Internet of Things (IoT) networks, and the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques.

Yogita (Senior Member, IEEE) received her Ph.D. degree from the Indian Institute of Technology (IIT) Roorkee, India, in 2016. She has served as an Assistant Professor in the Department of Computer Science and Engineering at the National Institute of Technology Meghalaya, India, from Jan. 2017 to Dec. 2022. She is an Assistant Professor in the Department of Computer Science and Engineering, National Institute of Technology Kurukshetra, India. Her research interests include machine learning, deep learning, data mining, and IoT applications for wireless networks and healthcare. She is a reviewer for various IEEE, Elsevier, Springer, and other journals and conferences.

Vipin Pal (Senior Member, IEEE) received his PhD degree from the Malaviya National Institute of Technology Jaipur, India. He is currently working as Assistant Professor in the Department of Computer Science and Engineering, National Institute of Technology Delhi, India. His research interests are IoT, Wireless Sensor Networks, Soft Computing, Data Mining. He is a reviewer of various IEEE, Elsevier, Springer, and other journals and conferences.

Satyendra Singh Yadav (Senior Member, IEEE), received his Bachelor of Engineering degree in Electronics and Communication Engineering (ECE) from Rajiv Gandhi Proudyogiki Vishwavidyalaya (RGPV), a state university of Madhya Pradesh, India, in 2012, and successively, the Ph.D. degree from the National Institute of Technology, Rourkela, India, in 2018. Dr. Yadav is the recipient of the prestigious ERASMUS MUNDUS fellowship. He was with the Instituto de Engenharia de Sistemas e Computadores Investigação e Desenvolvimento (INESC-ID), Instituto Superior Técnico Lisbon, Portugal, under India-EU ERASMUS MUNDUS NAMASTE PhD mobility project from 2015 to 2016. He served as a full-time faculty member at the Department of ECE, Indian Institute of Information Technology Design and Manufacturing Kurnool (IIITDM Kurnool), India, from July 2018 to June 2019, and at Indian Institute of Information Technology Vadodara (IIIT-Vadodara), India, for a short period of time. Dr. Yadav is an Assistant Professor at the Department of ECE, National Institute of Technology Meghalaya, India. His research interests include wireless communication, IoT networks, intelligent reflecting surfaces (IRS), and machine learning (ML) applications for 5G and beyond wireless systems. He is a reviewer for many IEEE, Elsevier, and Springer Transactions/Journals, as well as conferences. He has also served as a TPC member for many IEEE conferences.