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Optimizing Automatic Modulation Classification through Gaussian-Regularized Hybrid CNN-LSTM Architecture

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Abstract
This paper presents an innovative deep-learning model for Automatic Modulation Classification (AMC) in wireless communication systems. The proposed architecture integrates Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) networks, augmented by a Gaussian noise layer to mitigate overfitting. The integration of both networks seeks to enhance classification accuracy and performance by leveraging the unique capabilities of CNNs and LSTMs in capturing spatial and temporal features, respectively. The model is expected to distinguish between eight digital and two analog modulation modes. Experimental evaluation on the RadioML2016.10b dataset demonstrates a peak recognition accuracy of 93.2% at 18 dB SNR. Comparative analyses validate the superior performance of the proposed architecture. The Gaussian noise layer contributes significantly to a 3% performance improvement at 18 dB SNR. The model achieves recognition accuracy exceeding 96% for most modulation modes, highlighting its robustness. Finally, computational complexity analysis underscores the efficiency of the proposed architecture, reinforcing its practical viability.

1. Introduction

AMC is a technique that detects the modulation class of the received signal at the receiver of a wireless transmission system without prior information. In the current 5G communications, the receiver receives the signal from various directions, resulting in multipath fading that causes difficulty in signal identification. Today, multiple input multiple Output (MIMO) technologies are widely used in communications beyond 5G

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(B5G). As a result, the receiver will get a signal from more diverse sources, so a real-time system will be needed in the receiver to identify and classify the type of modulation [1]. AMC is expected to decrease overhead control as there is no need to share the modulation information between the receiver and the transmitter. In the literature, Researchers classify AMC algorithms into three categories: likelihood-based (LB) algorithms [2-5], feature-based (FB) algorithms [6-9], and artificial neural network algorithms [10-15]. LB algorithms detect the modulation type of the signal by comparing the likelihood value of the incoming signal to the predetermined modulation set. The FB algorithm extracts features from the incoming signal and identifies signal modulation by comparing features to threshold values or sending it to a pattern recognizer.

Recently, artificial intelligence has made great progress in many applications. The computational capacity of a single computer chip has significantly increased, which results in the widespread use of deep learning methods in modulation classification. In [16], deep learning has been presented for AMC using CNN to differentiate between ten distinct modulation techniques. Compared to the previous methods, CNN provides not only better accuracy than other methods but also flexibility in recognizing various forms of modulation. In [1], the authors propose the Convolutional LSTM Dense Neural Network (CLDNN) for AMC. The architecture of the network is formed by combining three different networks: CNN, LSTM, and Fully connected (FC) networks. Combining networks is justified by the fact that CNN performs quickly and lightly, LSTM is excellent at modeling time, and FC is suitable for feature mapping towards a more distinct space. The author of [17] created a ResNet approach to discriminate between 24 modulation methods., and the experiment produced impressive outcomes. An AMC scheme based on CNN and GRU has been proposed in [18]. The model could classify between 11 modulation modes with high recognition accuracy. The author in [19] developed a data-driven fusion strategy to enhance classification accuracy. This strategy combines two CNNs trained on distinct datasets. In [22], the authors introduced a new solution for the AMC issue, which combines residual and LSTM networks. The purpose of merging the two networks is to mitigate the vanishing gradient problem using ResNet and enhance temporal modeling using LSTM. The peak recognition accuracy achieved with this approach is 92% at 18 dB SNR.

This work presents a novel technique for AMC. The proposed architecture comprises two parallel networks, CNN and LSTM. Subsequently, the concatenation of these networks is followed by a Gaussian noise layer to mitigate overfitting. This architecture combines the strengths of CNNs in capturing spatial features with the capability of LSTMs in temporal modeling. The training and testing process relied on the RadioML2016.10b dataset. The simulation results of the proposed approach are contrasted with the findings of the latest AMC techniques. The performance analysis of this work focuses on recognition accuracy, confusion matrix, and execution latency.

The contribution of this study includes presenting a novel solution to the AMC issue , handling the overfitting problem through a Gaussian noise layer, Justifying the improvements of the model compared to the latest AMC models in terms of recognition

performance and execution latency, and finally assessing the model performance with various settings.

The content structure of the paper is as follows: Section 2 explains the signal model of the AMC system. Section 3 introduces the related works for AMC. Section 4 delineates the structural framework of the proposed method. Section 5 presents the performance of the proposed approach, focusing on recognition accuracy, and compares its simulation results with existing AMC models. Finally, the conclusion of this research is encapsulated in Section 6.

2. System model

The received wireless signal can be represented by:

$$r(t) = s(t) * h(t) + n(t) \qquad (1)$$

where $s(t)$ refers to the complex transmitted signal, For simplicity, the complex received signal $r(t)$ is frequently sampled in IQ format. $h(t)$ is the wireless time-variant channel impulse response, and $n(t)$ is the adaptive white Gaussian noise (AWGN).

2. Related Works

3.1. CNN-GRU approach.

The CNN-GRU model was presented in [18]. As shown in Fig.1, the structure of the model consists of two distinct networks, namely CNN and GRU. The CNN network comprises a trilogy of convolutional layers, with each layer followed by a 1*2 Max-Pooling layer, facilitating dimensional reduction, and concluding with a 0.4 dropout layer. The primary CNN layer is equipped with 512 filters, each with a 2*3 kernel size, while the second CNN layer encompasses 512 filters, each with a 1*3 kernel size. Lastly, the ultimate CNN layer encompasses 256 filters, each with a 1*3 kernel size. To establish a connection between the CNN and GRU components, the author utilizes global average pooling (GAP) instead of the flattened layer. GAP serves the purpose of reducing the dimensionality of the feature maps from the CNN, thereby preventing overfitting. The GRU network consists of two layers, with each layer containing 64 units and utilizing a ReLU activation function. The ultimate layer is a dense layer with SoftMax for output indication, thus concluding the model architecture.

3.2. Multi-channel convolutional long short-term deep neural network (MCLDNN)

The model was introduced in [24]. As illustrated in Fig.2, the approach encompasses three distinct networks: CNN, LSTM, and dense networks. The IQ input directly feeds into both the primary and secondary convolutional (Conv) layers. The model actively concatenated the outputs of these layers and then directed the resulting concatenation to the Conv3 layer. Subsequently, the result of the concatenation of Conv3 and Conv4 was passed through the Conv5
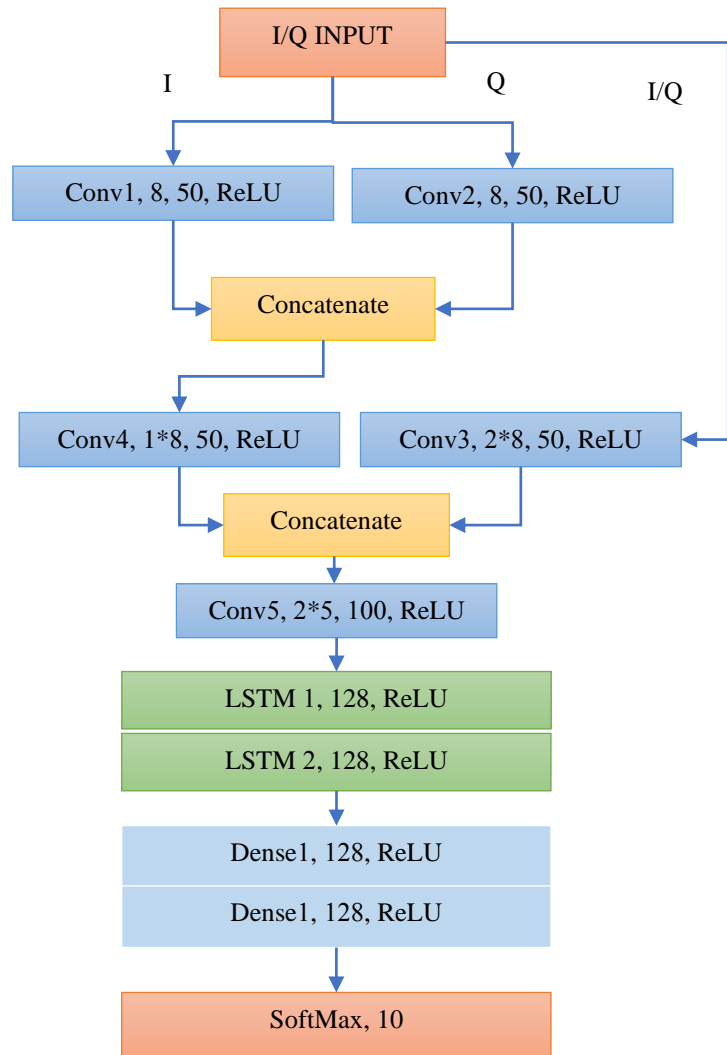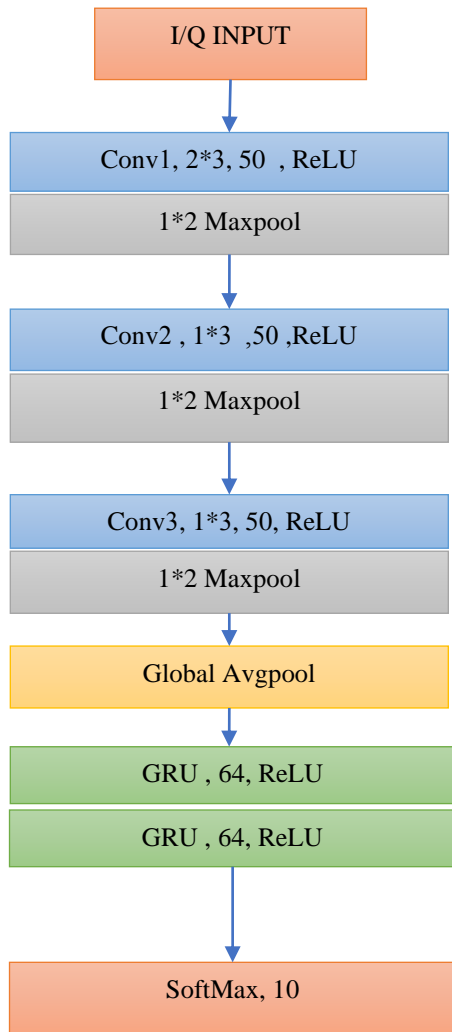
Fig. 1: CNN-GRU [18] model architecture.   Fig. 2: MCLDNN [24] model architecture

layer and ultimately fed to the LSTM network. The LSTM network consisted of two LSTM layers with 128 units and a ReLU activation function. The dense network includes two dense layers, each with 128 units and ReLU. The final layer was a dense layer with SoftMax for classification output.

3.3. CGDNET approach

The model was represented in [23]. As depicted in Fig.3, the model is constructed of three distinct networks, namely CNN, GRU, and dense networks. The CNN block consists of three Conv layers, with 50 filters each and a 1*6 kernel size, utilizing a ReLU activation function. Additionally, a 1*2 Max-Pooling layer follows this block. The concatenated outputs of the first and third Max-Pooling layers are subsequently fed into the GRU layer, comprising 50 units and employing a ReLU activation function. The GRU layer then passes its output through a dense layer, which contains 256 units, and applies another ReLU activation function. Finally, the model culminates in a dense layer with SoftMax, used for the output indication.
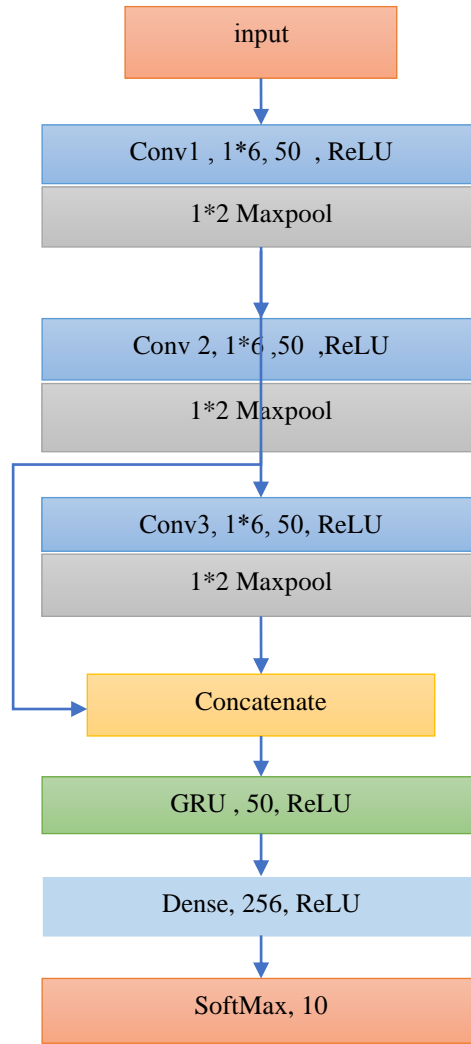
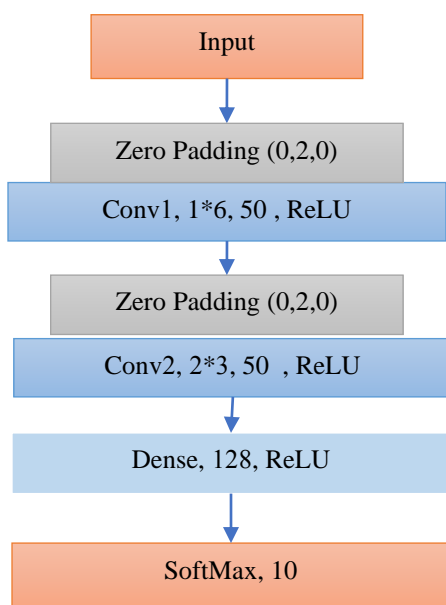Fig. 3: CGDNET [23] model architecture.
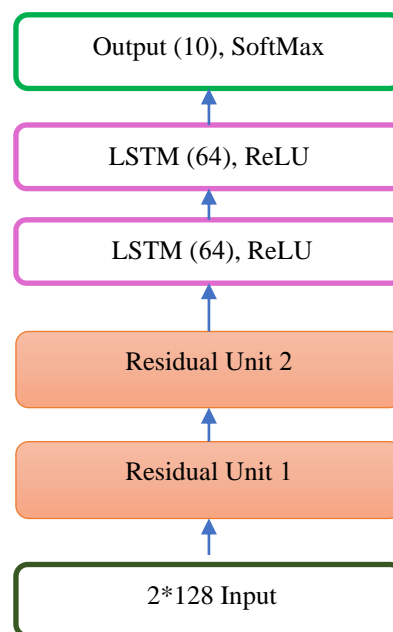

Fig. 4: VTCNN [25] model architecture.
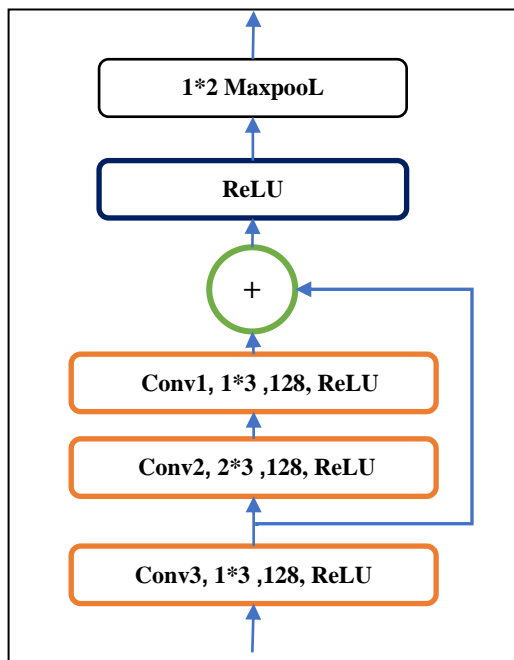

Fig. 5: ResNet-LSTM [22] model architecture.
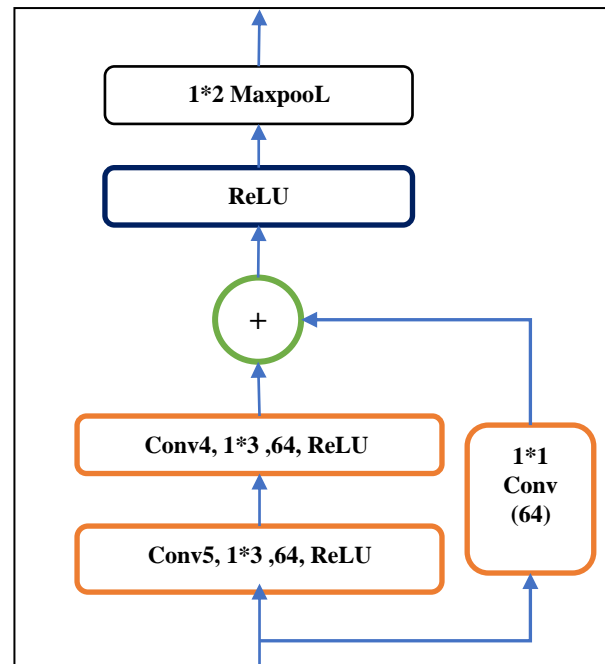
Fig. 6: Residual unit 1 architecture.

Fig. 7: Residual unit 2 architecture .

3.4. VTCNN2 approach

As illustrated in Fig. 4, the VTCNN model described in [25] comprises a CNN block with two convolutional layers, Conv1 and Conv2, each preceded by zero-padding layers. Conv1 employs 50 filters (1x3 kernel), while Conv2 utilizes 50 filters (2x3 kernel), both activated by ReLU. Subsequently, a dense layer with 128 units and ReLU activation is incorporated, leading to an output layer with SoftMax activation   function.

3.5. ResNet-LSTM approach

The approach was proposed in [22]. As shown in Fig.5, The architecture of the ResNet-LSTM model was designed by combining the ResNet network with the LSTM network. The motivation behind this hybrid approach stems from ResNet's capacity to facilitate feature propagation and mitigate overfitting, coupled with LSTM's capability to capture long-term dependencies. The residual segment includes two residual units, which are depicted in Fig. 6 and Fig. 7. The LSTM segment consists of two LSTM layers, with each layer housing 64 units that utilize the ReLU activation function.

4. The proposed method

4.1. Model description

As shown in Fig.8, the proposed model was generated by parallel CNN and LSTM networks followed by a Gaussian white noise layer to add a regularizing effect. The fusion of the two networks aims to boost classification accuracy and performance by exploiting the complementary strengths of CNNs and LSTMs in capturing spatial and temporal features,

respectively. The CNN network includes 4 convolutional layers, each of which contains a ReLU activation function. The initial Convolutional layer contains 64 (1*8) kernels and is followed by 2*2 max-pooling to reduce dimensionality. The Conv2 layer also has 64 (1*8) kernels without the max-pooling layer. The Conv3 layer includes 128 (1*3) kernels and is followed by a 1*2 max-pooling layer for dimension reduction. The final convolutional layer contains 128 (1*8) kernels without a max-pooling layer. A 0.2 dropout layer is added after the third and last convolutional layers to avoid overfitting. The LSTM network architecture includes two LSTM layers, each with 64 units and utilizing the ReLU function. After concatenating the outputs of the CNN and LSTM networks, a Gaussian noise layer with a standard deviation of 0.1 is incorporated to introduce regularization and mitigate overfitting. A standard deviation of 0.1 strikes a balance between introducing sufficient noise for regularization without overly disrupting the learning process. Finally, the last layer has 10 neurons with SoftMax for output indication.
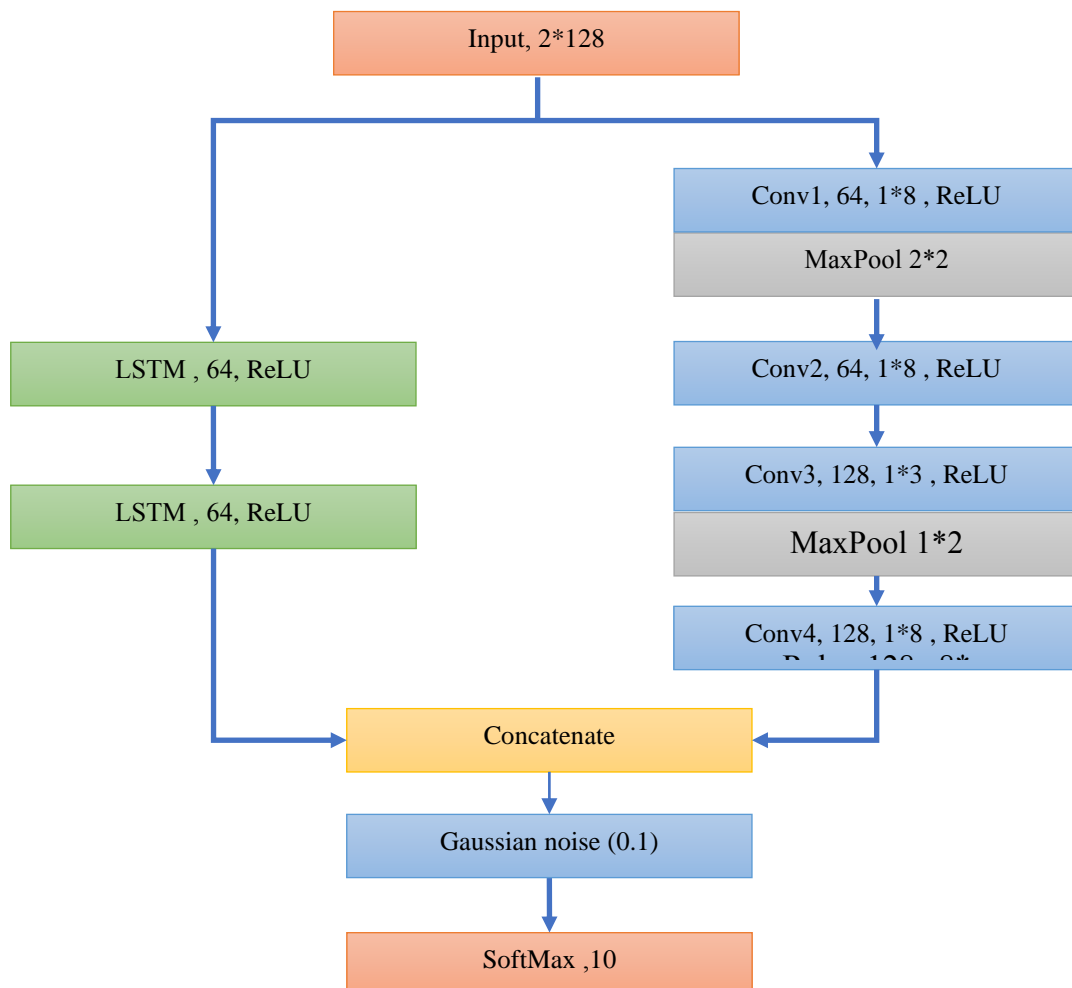
Fig. 8: Proposed model architecture

4.2. Dataset

The experimental results in this work rely on the RadioML2016.10b [20] dataset, generated by the GUR Radio toolkit. The dataset contains 1,200,000 samples from ten different modulation modes in IQ format with an SNR range of -20 to 18 dB. The modulation modes include eight digital modulation modes (- 8PSK - QPSK BFSK, - BPSK- CPFSK- QAM64 - PAM4 - QAM16) and two analog modulation modes (WBFM and AM-DSB). Each dataset sample is categorized by both SNR and modulation type, with a size of 2 * 128. All modulation modes in the dataset have the same number of samples.

4.3. Training and testing

In the training and testing process, 90% of the data is designated for training and the remaining 10% for testing .The validation dataset comprises 15% of the total training data. The dataset is divided evenly across all modulation modes by utilizing the stratified sampling technique. A learning rate of 0.0001, 64 batch size, Adam optimizer, cross-entropy loss function, and 35 epochs are adopted for the proposed approach during the training and testing. The structure of the proposed model is implemented using the Keras library and is run using Google Colab [21].

5. Results

5.1. Recognition accuracy.

The comprehensive analysis of recognition accuracy, as depicted in Fig. 9 and thoroughly elineated in Table 1, highlights a consistent and notable superiority of the proposed model over alternative methodologies across the specified SNR spectrum ranging from 0 dB to 18 dB. The proposed architectural framework achieves a notable apex accuracy of 93.2% at an SNR of 18 dB, surpassing benchmarks including VTCNN2[25], MCLDNN [24], CNN-GRU[18], CGDNET[23], and ResNet-LSTM[22] by differentials of 9.4%, 6.2%, 4.1%, 3%,
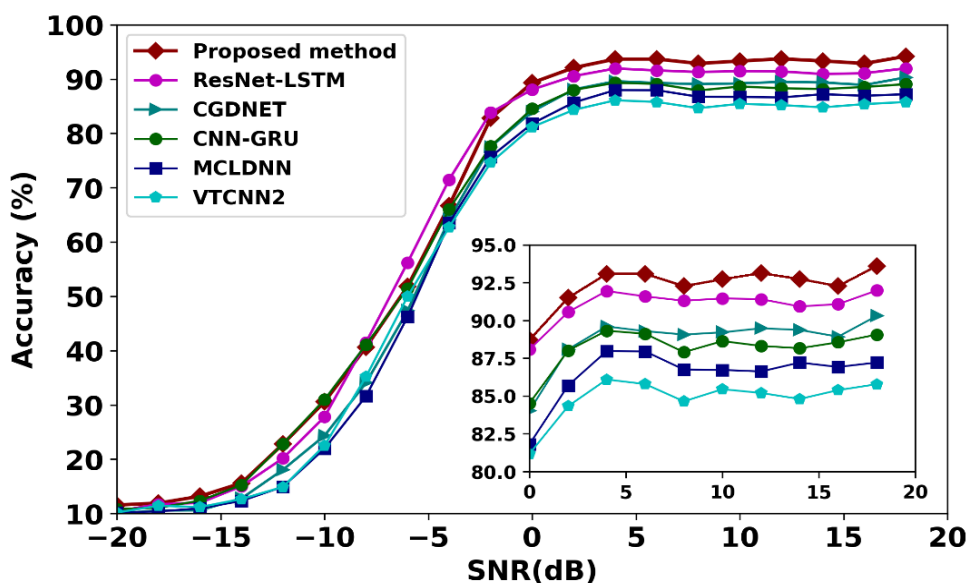

Fig. 9: The recognition accuracy of the six approaches.

Table 1: The recognition accuracy of the six approaches.

SNR (dB)	VTCNN2 [25] (%)	MCLDNN [24] (%)	CNN-GRU [18] (%)	CGDNET [23] (%)	ResNet-LSTM [22] (%)	Proposed Method (%)
-10	22.5	22	31	24.3	27.8	30
-2	74.6	75.7	77.6	77.5	85	84.6
2	84.3	85.8	88	88.1	90.55	91.1
6	85.78	87.9	89.1	89.28	91.6	92.7
12	85.2	86.6	88.3	89.48	91.4	92.72
18	85.8	87.2	89.1	90.2	92	93.2

and 1.2%, respectively. At an SNR of 12 dB, it demonstrates discernible enhancements of 7.5%, 6.12%, 4.42%, 3.24%, and 1.32% compared to VTCNN2, MCLDNN, CNN-GRU, CGDNET, and ResNet-LSTM. Transitioning to a moderate SNR of 6 dB, the proposed approach continues to excel, achieving an impressive accuracy of 92.7%, thereby outpacing VTCNN2 (85.78%), MCLDNN (87.9%), CNN-GRU (89.1%), CGDNET (89.28%), and ResNet-LSTM (91.6%). Navigating toward lower Signal-to-Noise Ratio (SNR) levels, specifically at -2 dB SNR, the proposed method exhibits resilience with an accuracy of 84.6%, surpassing established models, including VTCNN2 (74.6%), MCLDNN (75.7%), CNN-GRU (77.6%), and CGDNET (77.5%).

5.2. Confusion matrix

To assess the proficiency of the six approaches in discerning various modulation modes, confusion matrices at 18 dB SNR are presented in Fig. 10. The diagonal entries within these matrices denote the classification accuracy for each modulation mode. Notably, the proposed model achieves a classification accuracy exceeding 96% for most modulation methods, except WBFM. Furthermore, in the recognition of QAM16, it demonstrates improvements of 48%, 32%, 28%, 12%, and 1% over VTCCN2, MCLDNN, CNN-GRU, CGDNET, and ResNet-LSTM models, respectively. Additionally, it outperforms in QAM64 recognition, exhibiting advantages of 25%, 22%, 22%, 13%, 11%, and 8% over MCLDNN, VTCCN2, CGDNET, CNN-GRU, and ResNet-LSTM models, respectively.

5.3. Computation complexity

Table 2 presents a comparative analysis of the training and prediction times, as well as network sizes, for the six models. The proposed model has fewer parameters (314,890) compared to MCLDNN (9,500,646), VTCNN2 (5,698,714), CGDNET (654,476), and ResNet-LSTM (770,378), indicating potentially lower complexity and memory requirements. Furthermore, the proposed model demonstrates a substantial reduction in training duration per epoch, achieving 155 seconds, in stark contrast to the 517,416, 269, and 247 seconds required by the ResNet-LSTM, CNN-GRU, MCLDNN, and VTCNN2 models, respectively. Moreover, the proposed model's prediction time per sample is 50 μs less than CNN-GRU, 25 μs less than MCLDNN, 8 μs less than VTCNN2, and 5 μs less than ResNet-LSTM. Despite equal prediction times, the proposed model surpasses
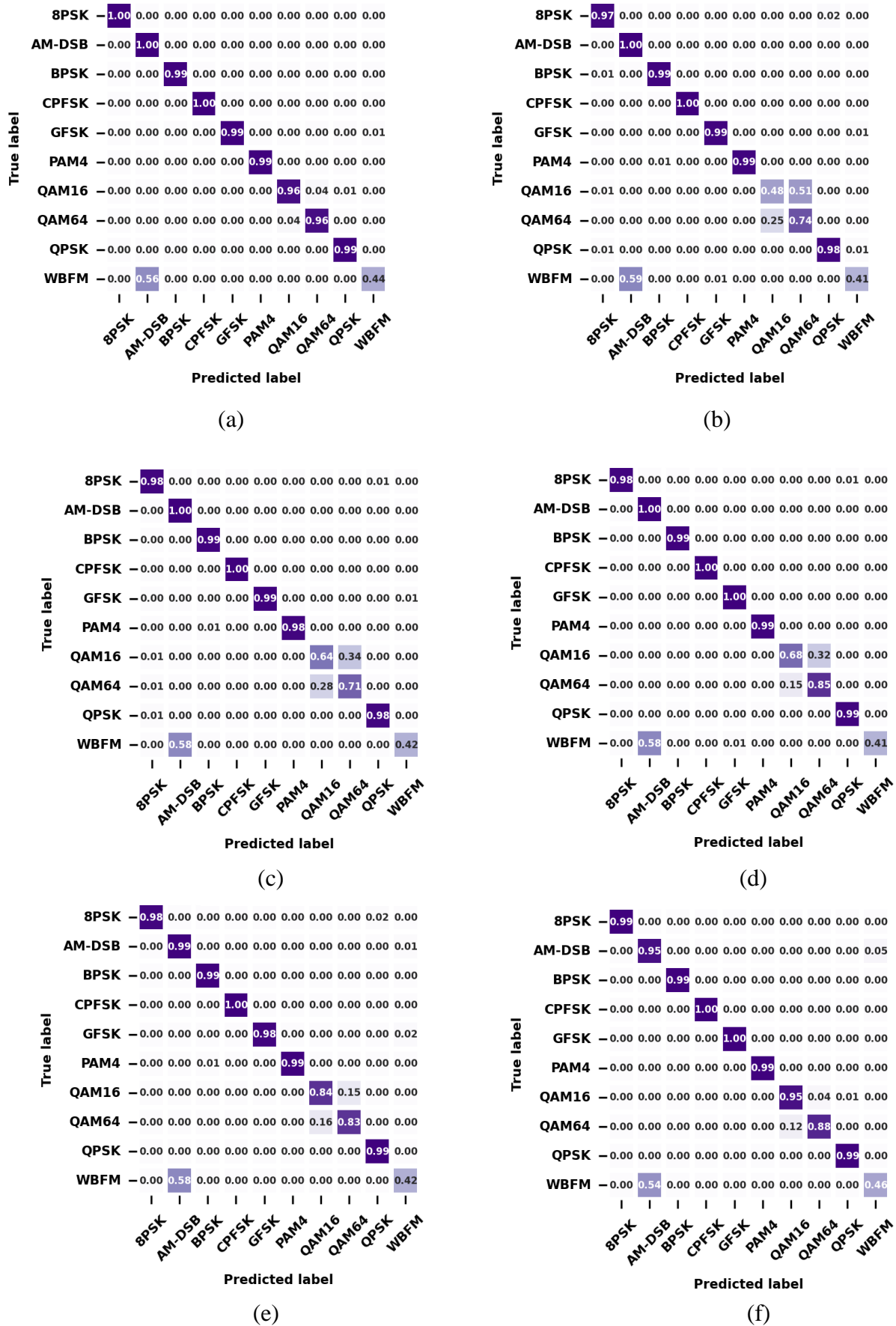
Fig. 10: The Confusion matrix for the six approaches at SNR = 18 dB: (a) the proposed approach (b) VTCNN2 [25] (c) MCLDNN [24] (d) CNN-GRU [18] (e) CGDNET [23] (f) ResNet-LSTM [22]

Table 2: The Computation complexity of the six models.

	MCLDNN [24]	VTCNN2 [25]	CNN-GRU [18]	CGDNET [23]	ResNet-LSTM [22]	Proposed Method
Total parameters	9,500,646	5,698,714	2,014,090	654,476	770,378	314,890
Training time/epoch	269s	247s	416s	108s	582s	155s
Prediction time/sample	200 мs	183 мs	225мs	175мs	180 мs	175 мs

CGDNET in overall classification accuracy and identifying complex modulations like QAM16 and QAM64, as mentioned in Sections 5.1 and 5.2. This makes it the preferred choice for precise modulation recognition.

5.4. Diverse Architectures and Factors: A Comprehensive Exploration

To boost efficiency, the effects of different architectures and factors are investigated. Fig. 11 examines the effect of integrating the Gaussian noise layer on the model's ultimate performance. It can be seen that The Gaussian noise layer helped the proposed approach to achieve a 3% improvement in performance at 18 dB SNR. This observation underscores the palpable effectiveness derived from the intentional integration of the Gaussian noise layer within the model's architectural framework. As demonstrated in Fig.12, nuanced adjustments to the CNN kernel size within the proposed architecture yield discernible effects on the ultimate recognition performance. Notably, the model characterized by a 1*8 kernel size attains the highest discrimination accuracy among its counterparts. Fig. 13 depicts the various depth settings for the CNN. Thorough scrutiny of these settings reveal the unequivocal superiority of the 4-layer CNN model, as evidenced by its superior performance relative to alternative depth configurations. This empirical observation
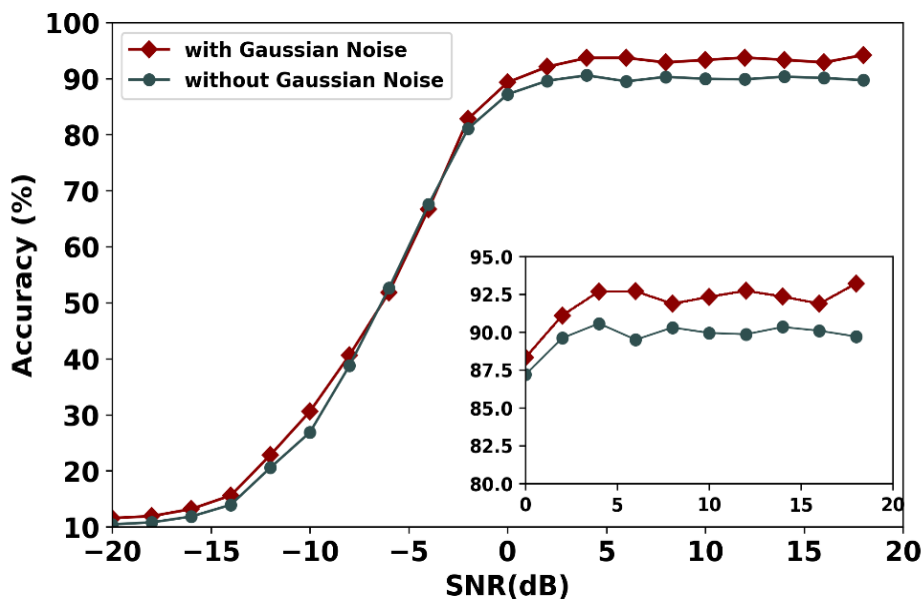

Fig. 11: The performance of the proposed model with and without gaussian noise layer.
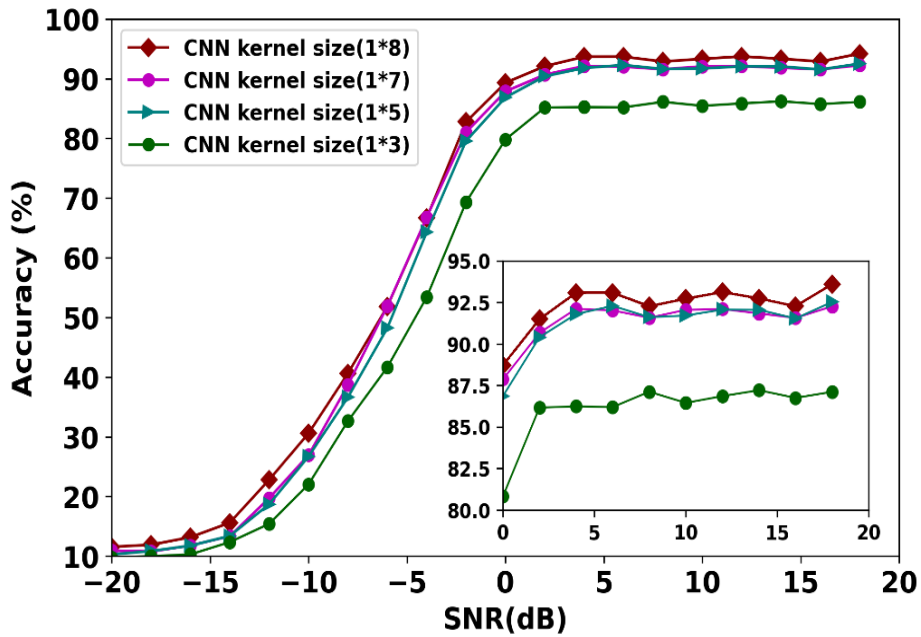
Fig. 12: The performance of the proposed model across different CNN kernel sizes.
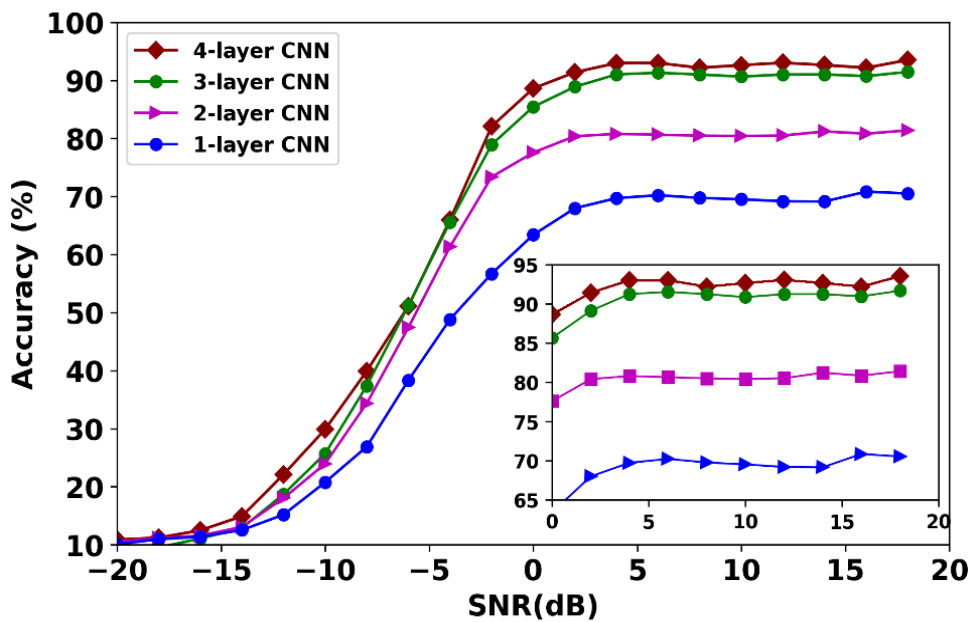

Fig. 13: The performance of the proposed approachh with different settings of CNN depth.

underscores the robustness and efficacy intrinsic to the specifically chosen 4-layer configuration within the CNN architecture. Simulation results for different LSTM depth settings are plotted in Fig. 14. It is observed that the peak recognition accuracy is reached by the two-layer LSTM network. Fig.15 portrays the training of the proposed model under various learning rate values. The simulation results demonstrate that the model trained with a learning rate of 0.0001 exhibits superior performance compared to its counterparts trained with alternative learning rate settings.
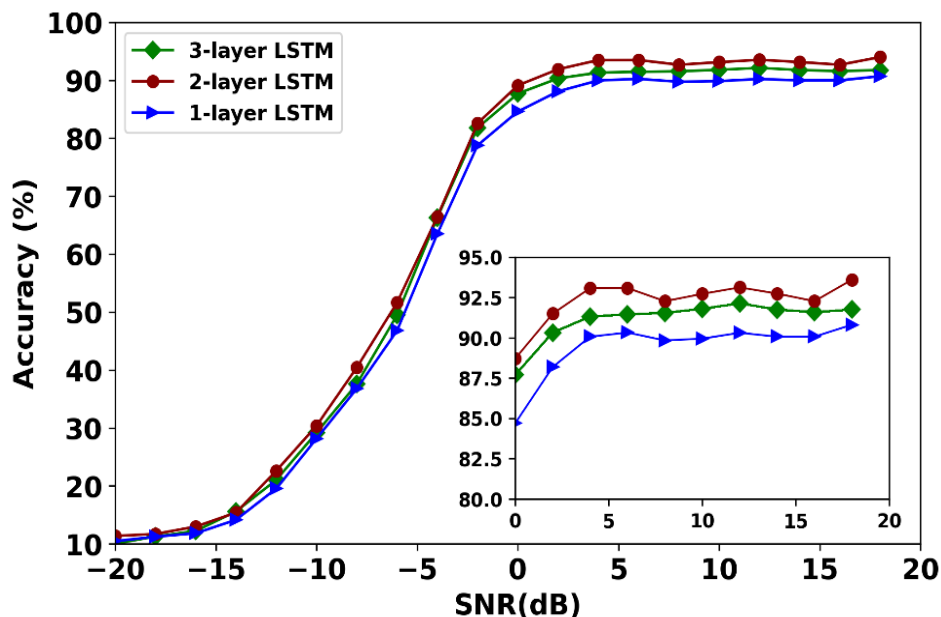
Fig. 14: The performance of the proposed approach with different settings of LSTM depth.
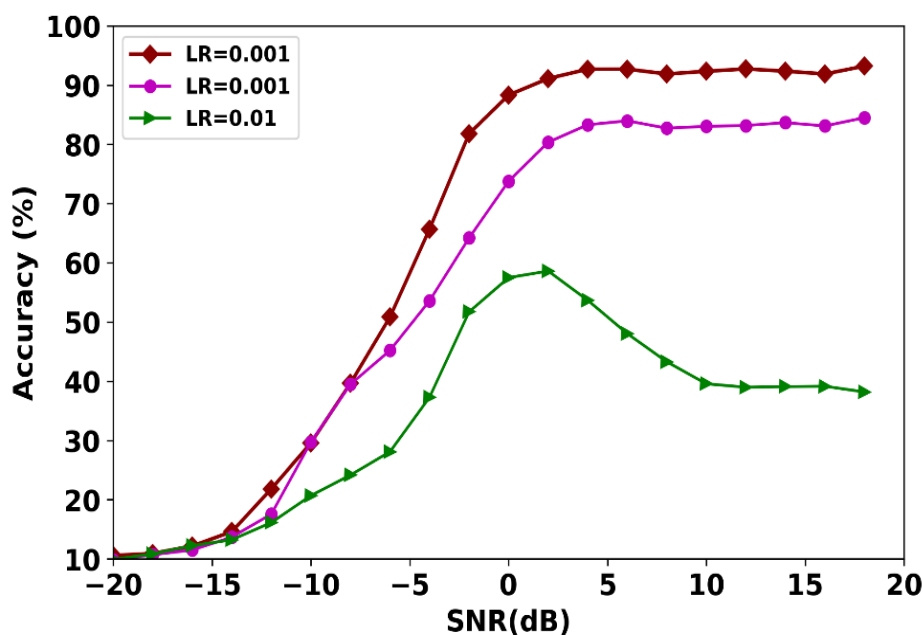

Fig. 15: The performance of the proposed model with different settings of learning rate.

6. Conclusion

In this paper, a new deep-learning approach for the AMC issue is provided. The model was developed with two parallel networks of CNN and LSTM followed by a Gaussian noise layer to reduce overfitting. The proposed architecture combines the strengths of CNNs in capturing spatial features with the capability of LSTMs in temporal modeling. The performance of the presented method is compared with five prior AMC approaches. The experimental results show that the maximum recognition accuracy obtained by the proposed

method is 93.2% occurring at 18 dB SNR, which is 9.4%,6.2%,4.1%, and 3%, more than VTCNN2, MCLDNN, CNN-GRU, CGDNET, respectively. Moreover, in terms of computational complexity, the prediction time of the proposed model for each sample is 50 ʍs, 25 ʍs, 8 ʍs, and 5 ʍs faster than CNN-GRU, MCLDNN, VTCNN2, and ResNet-LSTM models, respectively. In QAM16 recognition, the proposed approach shows improvements of 48%, 32%, 28%, 12%, and 1% over VTCCN2, MCLDNN, CNN-GRU, CGDNET, and ResNet-LSTM models, respectively. Moreover, in QAM64 recognition, it outperforms MCLDNN, VTCCN2, CGDNET, CNN-GRU, and ResNet-LSTM models by 25%, 22%, 22%, 13%, 11%, and 8%, respectively. The incorporation of the Gaussian noise layer substantially enhances performance, leading to a notable 3% improvement at 18 dB SNR. The future direction will be directed toward making models that have both accuracy and speed to suit the new generations in the field of wireless communications.

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" تحسين تصنيف التعديل التلقائي من خلال بنية CNN-LSTM الهجينة الغاوسية المنتظمة"

<u>الملخص العربي</u>

تقدم هذه الورقة نموذجًا مبتكرًا للتعلم العميق لتصنيف التعديل التلقائي (AMC) في أنظمة الاتصالات اللاسلكية . تدمج البنية المقترحة شبكات الشبكة العصبية التلافيفية (CNN) وشبكات الذاكرة طويلة المدى(LSTM) ، معززة بطبقة ضوضاء غاوسية للتخفيف من التجاوز .يسعى تكامل كلتا الشبكتين إلى تعزيز دقة التصنيف والأداء من خلال الاستفادة من القدرات الفريدة لشبكات CNN و LSTMsفي التقاط الميزات المكانية والزمانية، على التوالي .ومن المتوقع أن يميز النموذج بين ثمانية أوضاع تعديل رقمية ووضعين تناظريين . يوضح التقييم التجريبي لمجموعة بيانات RadioML2016.10b دقة التعرف القصوى البالغة 93.2% عند 18 ديسيبل SNR. التحليلات المقارنة تؤكد صحة الأداء المتفوق للبنية المقترحة .تساهم طبقة الضوضاء الغوسية بشكل كبير في تحسين الأداء بنسبة 3% عند 18 ديسيبل SNR. يحقق النموذج دقة التعرف تتجاوز 96% لمعظم أوضاع التعديل، مما يسلط الضوء على متانته .وأخيرا، يؤكد تحليل التعقيد الحسابي على كفاءة البنية المقترحة، مما يعزز صلاحيتها العملية.