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RESEARCH ARTICLE

ECG Classification Exercise Health Analysis Algorithm Based on GRU and Convolutional Neural Network

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ABSTRACT Sudden cardiac death (SCD) is one of the main causes of death in athletes during exercise and physical activity. By analyzing the results of the ECG classification, doctors can promptly detect the presence of cardiovascular diseases and implement appropriate treatment measures, thereby reducing disease progression and the occurrence of complications. Previous studies have typically used machine learning methods that often required manual feature selection, which could be subjective, time-consuming, and limited in scope. Additionally, the relationships between features may be overlooked, leading to a decrease in model performance. Therefore, our proposed approach automatically learns and selects relevant features, avoiding the issues associated with manual feature selection. In this paper, we introduce the Grunet deep learning network model, which utilizes convolutional neural networks to automatically extract features from ECG signals, thereby enhancing feature utilization and representation capabilities. Given the time-sensitive nature of ECG signals, we introduce gated recurrent units (GRU) to better capture these features. The gating mechanism of GRU helps manage information flow and facilitates capturing long-term dependencies. In our experiments conducted on the MIT-BIH Arrhythmia Database and the European ST-T Database, our proposed method achieved an overall classification accuracy of 99.47% on the European ST-T Database, with a precision of 98.76% and a recall of 97.92% on the MIT-BIH Arrhythmia Database. The classification accuracy for classes N and Q reached 100%. The experimental results demonstrate that our method outperforms existing techniques, significantly reducing the cost of manual intervention and improving the accuracy of heartbeat classification.

INDEX TERMS Electrocardiogram (ECG), gated recurrent unit (GRU), deep learning, convolutional neural network(CNN), classify.

I. INTRODUCTION

With an aging population, the number of patients with cardiovascular diseases is growing exponentially, necessitating efficient, accurate, and cost-effective automated electrocardiogram (ECG) diagnostics [1]. This is particularly crucial in populations with high-intensity activities, especially among athletes. Following long-term high-intensity training, athletes and young individuals often exhibit a series of ECG changes, such as bradycardia, early repolarization, increased ventricular voltage with or without T-wave inversion, atrioventricular conduction block, bundle branch block, and abnormal Q waves. Well-trained athletes typically show ECG changes due to physiological adaptations in response to exercise by the cardiac autonomic nervous system. These physiological ECG changes should be distinguished from uncommon and exercise-unrelated ECG patterns, which may indicate underlying cardiovascular diseases. Classifying these ECG

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abnormalities is beneficial for the cardiovascular management of athletes, aiding in diagnosing conditions, evaluating treatment plan risks, and reducing treatment costs [2].

In the realm of machine learning applications for ECG signal classification, relevant research dates back to the 1990s. For instance, Ince et al. proposed a machine learning-based system capable of automatically classifying patient-specific ECG signals, providing important insights for automated ECG signal analysis [3]. Additionally, a combined algorithm based on empirical mode decomposition and Hilbert transform for detecting R-peaks in ECG signals emerged in 2009. However, this algorithm is relatively complex and involves a substantial number of R-peak detection blocks [4]. Bulbul et al. employed various machine learning techniques for classifying P, Q, R, S, and T waves in ECG signals, integrating the BP (Back Propagation) algorithm with the MLP classifier, as well as the KA (Kernel-Adatron) algorithm with SVM classifier [5]. Furthermore, Aziz et al. proposed a novel algorithm utilizing two-event-related moving averages (TERMA) and fractional Fourier transform (FRFT) for better analysis of ECG signals [6]. Pham et al. utilized a random forest classifier to study electrocardiograms between 2 and 5 seconds, effectively leveraging temporal information rather than individual heartbeats, demonstrating good clinical applicability [7]. Papadogiorgaki et al. used k-Nearest Neighbors and Random Forests to classify electrocardiogram signals in 7 different abnormal and normal heart rate cases, achieving an average Area Under the Curve (AUC) of 99.9% [8]. While utilizing machine learning algorithms for ECG signal feature extraction requires expertise and experience, and feature engineering is challenging with high data quality requirements and sensitivity to noise and interference, early machine learning methods for ECG signal classification have laid the groundwork for the development of subsequent deep learning methods.

The powerful capability of deep learning in feature extraction has garnered significant attention in recent years, especially in the medical field, particularly in the classification of electrocardiogram (ECG) signals. These methods have proven effective in addressing the differences in ECG signals among patients, which is crucial for the early detection of cardiac diseases and accurate classification of abnormal ECG signals [9]. Researchers such as Acharya et al. have utilized deep convolutional neural networks to automatically identify five different types of heartbeats in ECG signals [10]. Kachuee et al. proposed a deep CNN-based heartbeat classification method capable of accurately classifying five types of arrhythmias according to the AAMI EC57 standard [11]. Oh et al.'s research combined CNN and LSTM, providing a new perspective for automated heartbeat diagnosis [12]. Deep learning not only plays a significant role in heartbeat diagnosis but also holds important value in the diagnosis of cardiovascular diseases such as myocardial infarction. Acharya et al. developed a diagnostic tool capable of accurately detecting normal and abnormal ECGs, achieving a high accuracy rate of 93.53% even in the presence of noise [13]. Additionally, they presented an innovative approach for diagnosing arrhythmias in multiple datasets within leads. Another study utilized the SqueezeNet model for image classification through transfer learning, converting ECG signals into scalegrams for training, yielding a validation score of 0.214 and a complete test score of 0.205 [14], [15] To improve the accuracy of automatic classification, Lv et al. proposed a deep learning method called SEN-BiLSTM. The method utilizes SENet and BiLSTM jointly for extracting morphological features of individual heartbeats, leading to higher adaptability and accuracy [16]. These research findings not only demonstrate the application value of deep learning in ECG signal classification but also pave the way for new possibilities in future medical diagnostic technologies.

The main contribution of this paper lies in the combination of CNN and GRU [17] in the initial stage to read simulated signals from the dataset. The signal is first processed using a Butterworth high-pass filter to reduce interference from power line noise, and then further processed using wavelet transform to reduce electromyographic interference. Automatic feature extraction is carried out using one-dimensional CNN, and the combination of GRU with CNN compensates for the insufficient time dependency in the CNN network for ECG signals. Given the potential presence of long-term dependencies in ECG signals, recurrent neural networks can capture these long-term dependencies, thereby improving classification performance and enhancing the network's resistance to noise, thus improving its robustness.

II. RELATED WORK

A. NOISE REDUCTION

Electrocardiography (ECG), as a core diagnostic tool in the medical field, is primarily used for monitoring and diagnosing heart function. It provides direct evidence of the heart's health by accurately capturing and recording the heart's electrical activity. In clinical practice, ECG plays an irreplaceable role in the diagnosis of heart diseases such as arrhythmia and ventricular premature beats.

However, the original ECG signals are not pure and are often subject to various external interferences, collectively referred to as "noise." This noise can originate from multiple sources, such as interference from electromyographic signals, baseline fluctuations, electromagnetic interference from power lines, noise caused by poor electrode-skin contact, and motion artifacts caused by slight patient movement or physiological activities (such as muscle contractions or breathing). Additionally, thermal noise from the ECG acquisition equipment or other internal interferences may also affect the signal quality.

To eliminate this noise, researchers have developed various algorithms and techniques. Some algorithms are based on classical digital signal processing techniques, such as Fourier analysis, to improve signal quality by identifying and filtering out noise within specific frequency ranges. Adaptive filters are also commonly used tools that can automatically adjust their parameters based on input signals to better eliminate noise [18].

With the rapid development of artificial intelligence and machine learning technologies, neural networks and other modern statistical techniques have also been introduced to ECG denoising. These methods, by learning from a large amount of noisy and noise-free ECG data, can automatically identify and eliminate noise components.

Researchers such as Boudraa et al. [19], [20] have conducted in-depth studies on the application of wavelet soft and hard thresholding methods in EMD denoising. They conducted denoising experiments on various typical signals, including ECG signals, and compared the results with median filtering and wavelet denoising. The results showed that the EMD denoising method exhibited significant performance advantages. Tang et al [21], among others, combined EMD with wavelet soft and hard thresholding methods to conduct a detailed analysis of denoising effects on ECG signals. The results indicated that compared to wavelet denoising, EMD demonstrated superior denoising effects in signal reconstruction [22]. In the extraction of fetal ECG signals, Cao et al. [23] proposed a nonlinear adaptive denoising framework based on time convolutional neural networks (CNN) for effectively extracting fetal ECG signals from maternal abdominal ECG recordings. Cui et al. formed the optimal feature set by the features extracted by one-dimensional CNN and discrete wavelet transform, and the average classification accuracy was as high as 98.35% [24]. Furthermore, in 2022, Yang et al. introduced a denoising method for electroencephalogram signals based on sparse representation component analysis. The residual was taken as noise, and the denoised signal was obtained as the product of a dictionary and sparse coefficients. This method can be applied for the separation and identification of electrocardiogram signals, holding significant importance for clinical research and pathological diagnosis [25].

In response to the noise characteristics in ECG signals, we employ a Butterworth high-pass filter for denoising. The Butterworth high-pass filter has a smooth frequency response characteristic, effectively removing low-frequency noise and baseline drift while retaining the high-frequency components of the signal. Chest movements caused by respiration may lead to changes in ECG signals, resulting in respiratory motion artifacts that affect the analysis and diagnosis of the ECG. Therefore, after filtering with the Butterworth high-pass filter, we further utilize wavelet transform to process the signal, reducing the impact of respiratory motion on the ECG signal. By combining the use of the Butterworth high-pass filter and wavelet transform, we can achieve effective denoising of ECG signals, thereby improving the accuracy and reliability of the electrocardiogram.

B. CNN IN ECG CLASSIFICATION

The machine learning paradigm is heavily influenced by feature engineering and feature selection. Its fundamental principle is to integrate all data information into the signal, enabling machine learning algorithms to identify and learn specific patterns. This principle forms the basis of deep learning, particularly one-dimensional networks such as convolutional neural networks (CNN) [26]. Due to the potential and prospects of deep learning, researchers [27] have begun to utilize these technologies for the detection and classification of various chronic diseases. Since the emergence of Unet [28] in medical image processing, convolutional neural networks have once again become a research focus. In 2020, Zhao et al. [29] and their team utilized a 24-layer convolutional neural network to extract hierarchical features through different sizes of convolutional kernels and combined them with softmax for classification, achieving significant results. However, this method solely relies on convolutional neural networks and does not fully exploit the long-term dependencies in ECG signals. Addressing this issue, Acharya et al. proposed an automatic arrhythmia classifier [30]. Subsequently, Acharya et al. [31] introduced an automatic CNN model for distinguishing two different types of ventricular arrhythmias. The model exhibited high accuracy (93.18%), high sensitivity (95.32%), and high specificity (94.04%). Additionally, Kachuee et al. [27] utilized deep residual CNN for arrhythmia classification and combined t-SNE for feature visualization. Following the AAMI EC57 standard, this method accurately identified five types of arrhythmias in the MIT-BIH arrhythmia database, with an accuracy rate of up to 95.9%. This research provides strong support for automatic arrhythmia classification. Similar to deep residual CNNs, Wu et al. proposed a 12-layer deep one-dimensional convolutional neural network, which exhibits good robustness and noise resistance. This model plays a positive role in clinical practice [32].

C. RECURRENT NEURAL NETWORKS

Recurrent neural networks (RNNs) have shown excellent performance in handling sequential data such as wave signals, natural language, and videos [33]. Due to its unique recursive structure, RNN can analyze and produce output based on historical data. Bavani et al. [34] introduced an enhanced RNN in the classification of arrhythmia diseases, aiming to effectively combine static and dynamic data features. However, the short-term memory characteristics of RNN lead to issues of time consumption and data loss when dealing with long time series. Long Short-Term Memory (LSTM), as a variant of RNN, with its powerful learning capability, can handle longer dependencies [35]. LSTM has demonstrated outstanding performance in various problems and is widely used in big data analysis. Ullah et al. [36] utilized LSTM for multi-class classification of large video datasets, achieving over 90% classification accuracy. Similarly, Zhou et al. [37] applied LSTM in the field of natural language processing, obtaining over 80% classification accuracy. Zheng et al. proposed a novel classification method that combines a 24-layer deep convolutional neural network with bidirectional long short-term memory to delve deeper into the hierarchical and time-sensitive features of electrocardiogram data [38]. Furthermore, the combination of convolutional neural networks (CNN) and RNN has garnered significant attention [39]. Similar to LSTM, a Gated Recurrent Unit (GRU) has fewer parameters and lower computational costs, controlling the flow of information through reset and update gates. It has a faster training speed and requires less memory than LSTM. Therefore, this study combines GRU units with convolutional neural networks to automatically capture long-term dependencies in ECG signals, enabling faster training and reducing the risk of overfitting.

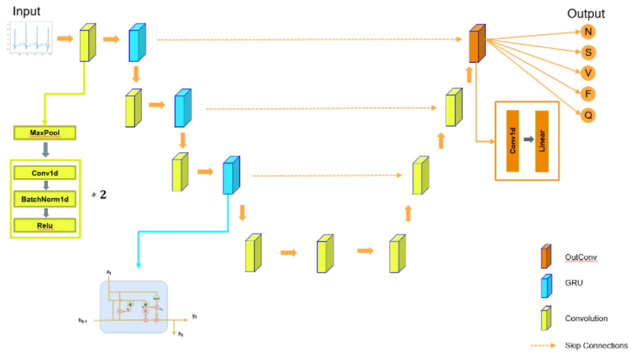

FIGURE 1. Overall network structure.

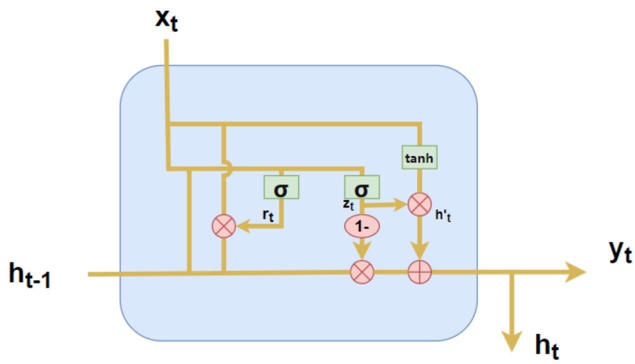

FIGURE 2. GRU structure.

III. METHODOLOGY

The Grunet network designed in this study consists of an encoder and a decoder, forming an end-to-end network structure capable of automatically learning features from ECG signals without the need for manually designing feature extractors, thus reducing the requirement for domain-specific expertise. As shown in Fig 1, we employ three times downsampling for ECG signal feature extraction, with each downsampling module containing a 2×2 max-pooling layer, two BatchNorm layers, and two one-dimensional convolutional layers. After each downsampling, we introduce GRU units to enhance the network's ability to capture long-term dependencies within the ECG signals. In the upsampling module, we utilize bilinear interpolation for feature restoration and employ Concatenation to merge corresponding position features, enabling the utilization of more feature information during the upsampling process for improved classification performance. Finally, the classification is performed using the OutConv module, which includes a one-dimensional convolutional layer and a linear layer.

As shown in Figure 2, the GRU combines the input information x_t at the current time and the hidden state h_{t-1} at the previous moment to obtain the output y_t of the currently hidden node and pass the currently hidden state h_t to the next node. The GRU removes the cell state in favor of a hidden state to transmit information, so its parameters are lowered, which makes training faster and less prone to overfitting.

The h_t is determined by two parts, the first is to update the door z_t, and the second is to reset the door r_t.

First, using Equation 1, the r_t is calculated:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{1}$$

Then, using the value of the r_t, the candidate hidden state h'_t is calculated, as shown in Equation 2:

$$h'_t = tanh(W \cdot [r_t, x_t]) \tag{2}$$

The formula for updating the door z_t is as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{3}$$

We used one layer of GRU, so we used h_t as input to the next layer of convolution to extract features further.

IV. EXPERIMENT

A. DATASET

We use the MIT-BIH Arrhythmia Database from the Massachusetts Institute of Technology and the European ST-T Database from the European Society of Cardiology as the dataset for our experiments. The MIT-BIH database consists of 48 half-hour two-channel ambulatory ECG recordings, with each channel sampled at 360 Hz and digitized with an 11-bit resolution within a range of ± 10 mV. Each record, totaling approximately 110,000 annotations, was independently annotated by two cardiac experts. The European ST-T Database includes 367 episodes of ST segment change, and 401 episodes of T-wave change, with durations ranging from 30 seconds to several minutes, and peak displacements ranging from 100 microvolts to more than one millivolt. Each record is two hours in duration and contains two signals, each sampled at 250 samples per second with 12-bit resolution over a nominal 20 millivolt input range.

B. DATA PREPROCESSING

To address baseline drift in the ECG signals caused by incomplete skin-electrode contact or motion artifacts, we applied a Butterworth high-pass filter for noise reduction. The Butterworth high-pass filter, known for its smooth frequency response characteristics, effectively removes baseline drift. The processing effect is shown in figure 3 and figure 4.(The two datasets are processed in the same way, and only the MIT-BIH dataset preprocessing results are shown here)

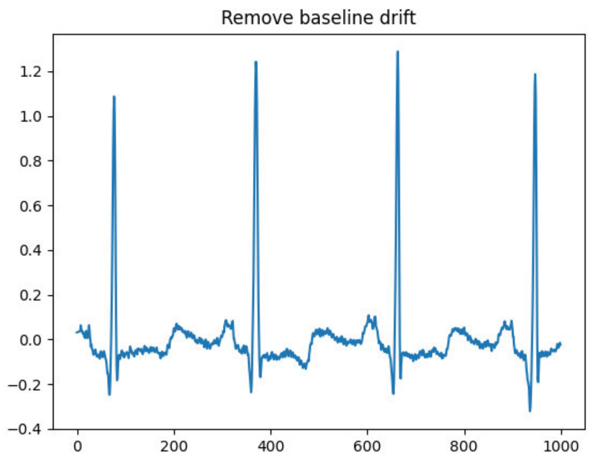

FIGURE 3. Signal after removing baseline drift.

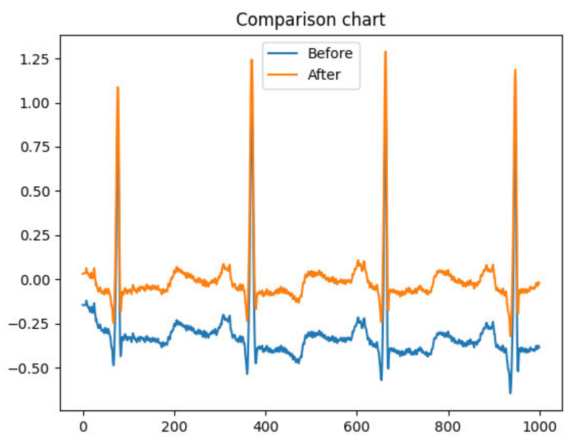

FIGURE 4. Comparison of the processed signal with the original signal.

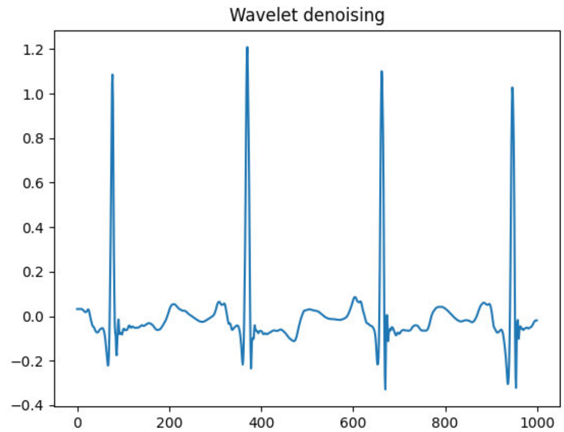

FIGURE 5. Signal diagram after wavelet transformation.

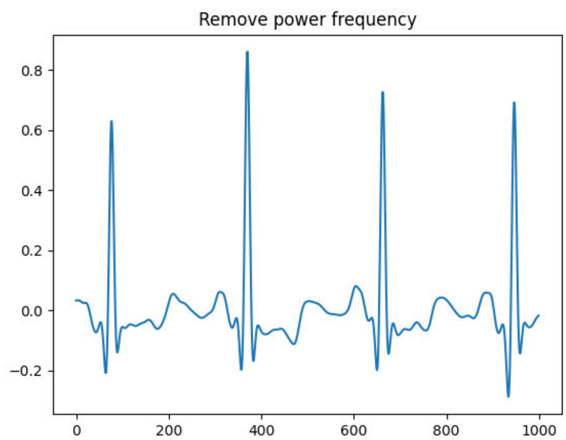

FIGURE 6. Signal diagram after low-pass filtering.

Chest movements due to respiration can lead to changes in ECG signals, producing respiratory motion artifacts that affect the analysis and diagnosis of ECGs. We used the wavelet transform to reduce the effect of respiratory motion on the ECG signal. The effect is shown in figure 5:

In the process of ECG signal acquisition, it will be interfered with by the electromagnetic field generated by the operation of the power system, including transmission lines, transformers, motors, and other equipment, resulting in a noise of 50/60Hz, which is called power frequency interference. To remove the interference caused by these noises, we use Butterworth's low-pass filtering can also be used to remove power frequency interference, that is, to remove the high-frequency part of the signal and smooth out the signal. The effect is shown in figure 6:

According to the standards provided by the AAMI (American Heart Association), heartbeats are divided into five categories, which are N, S, V, F, and Q. Therefore, we first select the data with a specific label that is required for each record and discard the points with the remaining labels. Since a full heartbeat cycle is about 0.6 seconds to 0.8 seconds, we intercepted 300 data points before and after the R wave, which is just enough to meet the requirements of the heartbeat classification and meet the AAMI standard.

C. EVALUATION INDICATORS

We use accuracy, recall, and F1 score as evaluation metrics to assess the performance of the network model. Where TP (True Positive) represents the number of samples correctly predicted as positive by the model, TN (True Negative) represents the number of samples correctly predicted as negative, FP (False Positive) represents the number of samples incorrectly predicted as positive, and FN (False Negative) represents the number of samples incorrectly predicted as negative by the model.

Accuracy is a commonly used evaluation metric to measure the predictive accuracy of a classification model across the entire dataset. The accuracy metric can be calculated using the following formula:

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \tag{4}$$

Precision measures how many of the samples that the model predicts to be positive are true positives. The precision

TABLE 1. Comparison of the effects of different filters and their combinations on the classification effect.

Method	Accuracy	Precision	Recall	F1 score
Butterworth low-pass filter	0.9796	0.9441	0.9111	0.9257
Butterworth high-pass filter	0.9861	0.9684	0.9303	0.9472
Wavelet transform	0.9823	0.9516	0.9195	0.9340
high-pass filter + low-pass filter	0.9816	0.9426	0.9161	0.9285
high-pass filter + Wavelet transform	0.9834	0.9513	0.9207	0.9348
low-pass filter + Wavelet transform	0.9840	0.9613	0.9225	0.9402
low-pass + high-pass + Wavelet	**0.9863**	**0.9707**	**0.9374**	**0.9525**

can be calculated by the following formula:

$$PRE = \frac{TP}{TP + FP} \tag{5}$$

Recall measures how many of the true positive examples are successfully predicted by the model to be positive. The recall rate can be calculated by the following formula:

$$REC = \frac{TP}{TP + FN} \tag{6}$$

The F1 score is a blended average of precision and recall, taking into account the performance of precision and recall. The F1 score can be calculated by the following formula:

$$F1 = \frac{2 \times PRE \times REC}{PRE \times REC} \tag{7}$$

D. EXPERIMENTAL RESULTS

1) NOISE REDUCTION EXPERIMENT

We use the Butterworth high-pass filter to eliminate the interference of baseline drift and further use the Butterworth low-pass filter to process the interference of the power frequency for noise reduction. The processed signal is used as the input of the wavelet transform, and through the final wavelet transform, we successfully reduce the effect of respiratory artifacts in the ECG signal on the classification effect. The specific experimental results are shown in table 1.

This series of noise reduction experiments provides important data preparation for our subsequent construction of the network structure. Through these experiments, we verified the importance of noise reduction processing to improve the classification effect and laid the foundation for the next work. These results provide strong support for our research and provide an important reference for our subsequent network structure construction and classification effect.

TABLE 2. Comparison of the effects of different modules and their combinations on the classification effect.

Model	Accuracy	Precision	Recall	F1 score
RNN	0.9863	0.9707	0.9374	0.9525
CNN	0.9932	0.9789	0.9779	0.9765
GRU	0.9871	0.9728	0.9443	0.9574
GRU+CNN（Grunet）	**0.9956**	**0.9876**	**0.9792**	**0.9833**

TABLE 3. Comparison of the average accuracy of the proposed architecture with other existing architectures in classification.

Paper	Database	Model	Accuracy
Farag et al. [41]	MIT-BIH	CNN+STFT	98.85%
Madan et al. [42]	MIT-BIH	2D-CNN-LSTM	98.1%
Khan et al. [43]	MIT-BIH	ResNet+SMOTE	97.9%
Lu et al. [44]	MIT-BIH	CNN	96.83%
Zheng et al. [45]	MIT-BIH	CNN-LSTM	97.96%
Hsu et al. [46]	MIT-BIH	AlexNet and ResNet	96.28%
Gaddam et al. [47]	MIT-BIH	AlexNet	93.44%
Bavani et al. [35]	MIT-BIH	DT+RNN	91%
Atal et al. [48]	MIT-BIH	optimized CNN	93.19%
Wasimuddin et al.[49]	European ST-T	CNN	96.29%
Jiang et al.[50]	European ST-T	MMNNS	93.7%
Barbosa et al.[51]	European ST-T	CNN+MLP	98%
Merdjanovska et al.[52]	European ST-T	CNN	99.39%
Our	**MIT-BIH**	**CNN+GRU**	**99.56%**
Our	**European ST-T**	**CNN+GRU**	**99.47%**

2) ABLATION EXPERIMENT

After determining the data processing approach, we conducted ablation experiments to validate the effectiveness of the modules. We separately employed replacement schemes using RNN and CNN and then combined them to verify the final classification performance. According to the results in Table 2, our average classification accuracy reached 99.56%, with a precision of 98.76%, recall of 97.92%, and an F1 Score of 98.33%. These results indicate that our modules played a crucial role in improving classification accuracy after undergoing ablation experiment validation. This further confirms the effectiveness of our method in data processing and module combination, providing strong support for our research work.

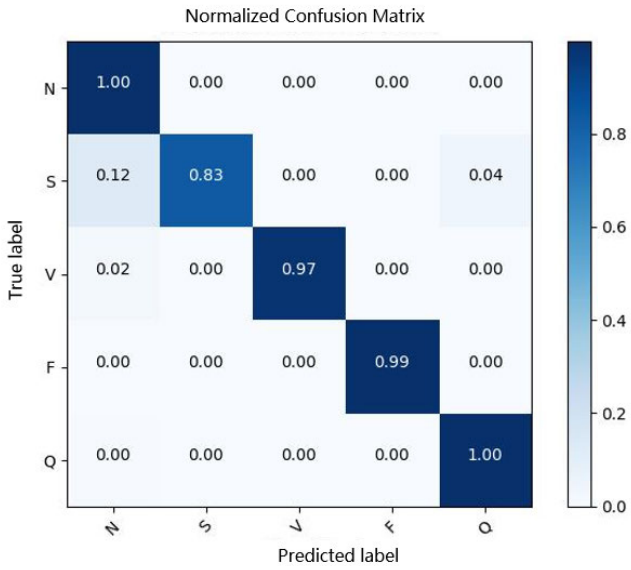

FIGURE 7. MIT-BIH classification confusion matrix.

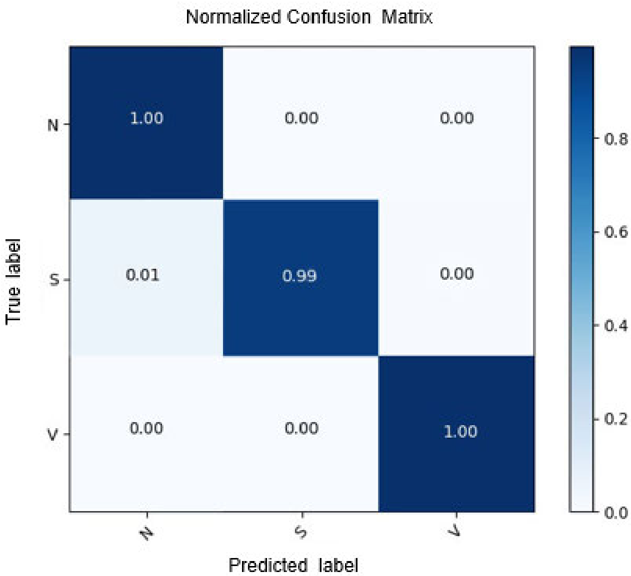

FIGURE 8. European ST-T classification confusion matrix.

3) COMPARATIVE TEST

To validate our proposed method, we compared our results with current and standard methods in terms of datasets, methodology, and accuracy, as shown in Table 3. It is worth mentioning that our method has achieved good results in MIT-BIH Arrhythmia Database and European ST-T Database, respectively, and has obvious advantages over other methods. These results suggest that the proposed method has an important competitive advantage in the current research field and maybe a strong choice for future research and application. These findings provide strong support for the feasibility and effectiveness of our method and lay a solid foundation for further development in this field.

We plotted the confusion matrix for the five-class classification of the MIT-BIH Arrhythmia Database. According to figure 7, it can be observed that the model categorizes the electrocardiogram signals into five classes: N, S, V, F, and Q, and displays the classification performance among them. The confusion matrix is normalized, representing the proportion of predictions for each class. The model perfectly classifies instances of the N and Q categories, with a normalized value of 1.00. The S category exhibits good classification performance, with a correct classification proportion of 0.83, but also indicates some misclassifications, with 12% of S instances being incorrectly classified as N and 4% as Q. The V category has a correct classification proportion of 0.97, with only 2% of instances being misclassified as N. The F category also demonstrates very high classification performance, with a correct classification proportion of 0.99. Overall, the classification model's performance is quite good, with the highest misclassification rate occurring in the S category. However, even for this category, the majority of instances are correctly classified.

Due to the small number of instances in the F and Q categories in the European ST-T Database, to address the data imbalance issue and reduce the disparities it may cause, we conducted a three-class classification on the electrocardiogram signal data using Grunet to evaluate the model's performance. We plotted the three-class confusion matrix for the European ST-T Database, as shown in Figure 8, where we categorized the signals into three classes: N, S, and V. The correct classification proportions for the N and V classes were both 1, while the S class achieved a correct classification proportion of 0.99. This represents a significant improvement compared to the MIT-BIH database, possibly due to the reduced number of classes, which decreased confusion during classification. This also provides new insights for future related research, highlighting the importance of addressing data imbalance issues and defining key classification objectives in classification tasks.

V. CONCLUSION

In this study, we designed an encoder-decoder structure that can extract and fuse multi-scale features at different levels. This structure has significant advantages in processing ECG signals because ECG signals contain features of various frequencies and scales, which are crucial for accurately classifying electrocardiograms. In this way, our model can comprehensively understand and capture the complex features in ECG signals, thereby improving classification accuracy.

The Grunet network we proposed is end-to-end trainable. This means the model can directly learn and extract useful features from raw ECG signals without the need for tedious manual feature extraction processes. This feature greatly simplifies the model's learning process and improves its efficiency and accuracy.

Furthermore, we utilized GRU to handle time series data. GRU units are particularly suitable for processing data with long-term dependencies, which is crucial for understanding and classifying ECG signals. Through GRU units, the model can better understand and capture the temporal relationships between different parts of the ECG signal, further enhancing classification accuracy.

The classification of ECG signals holds immeasurable value in the diagnosis and monitoring of heart diseases. With the continuous advancement of medical technology, the application of deep learning in the medical field is becoming increasingly widespread. In our future work, we will continue to explore the application of deep learning in ECG signal analysis, strengthen feature extraction, and further improve the accuracy of classifying the S category.

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