Research Article

Identification of Arrhythmia by Using a Decision Tree and Gated Network Fusion Model

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In recent years, deep learning (DNN) based methods have made leapfrogging level breakthroughs in detecting cardiac arrhythmias as the cost effectiveness of arithmetic power, and data size has broken through the tipping point. However, the inability of these methods to provide a basis for modeling decisions limits clinicians’ confidence on such methods. In this paper, a Gate Recurrent Unit (GRU) and decision tree fusion model, referred to as (T-GRU), was designed to explore the problem of arrhythmia recognition and to improve the credibility of deep learning methods. The fusion model multipathway processing time-frequency domain featured the introduction of decision tree probability analysis of frequency domain features, the regularization of GRU model parameters and weight control to improve the decision tree model output weights. The MIT-BIH arrhythmia database was used for validation. Results showed that the low-frequency band features dominated the model prediction. The fusion model had an accuracy of 98.31%, sensitivity of 96.85%, specificity of 98.81%, and precision of 96.73%, indicating its high reliability and clinical significance.

1. Introduction

Arrhythmia is a type of heart disease characterized by an irregular heartbeat with multiple categories and complex waveforms, making it difficult to accurately detect and locate waveforms and to set up classification features.

The traditional approach to arrhythmia identification is based on feature extraction (e.g., time-domain morphological features, frequency-domain features, and cardiac rhythm features) and the use of various machine learning classifiers, such as decision trees [1], nearest neighbor [2], support vector machines (SVMs) [3], logistic regression [4], and Artificial Neural Network [5]. These methods can often uncover potential explanatory factors hidden in observed sensory data, form abstract concepts, and reach consensus on recognition tasks [6]. However, feature design relies on the a priori knowledge of the designer.

In recent years, DNN technology has demonstrated excellent performance in the identification of cardiac arrhythmias. Several studies using recurrent neural network (RNN) variants of long short-term memory (LSTM) [7], convolutional neural network (CNN) [8], and other hybrid models have shown excellent performance in simplifying the input high-dimensional data into a compact low-dimensional representation space by automatically adjusting parameters using optimization algorithms. DNN creates end-to-end learning systems that use ECG signals as inputs and arrhythmia class predictions as outputs to automatically
learn complex representative features from the data, reducing overreliance on artificially designed features. However, DNN, as an end-to-end black box model, has difficulty interpreting the significance of numerous parameters and the output of hidden neurons.

While the DNN black box approach may be sufficient in many use cases, models in sensitive medical areas need to provide a trustworthy basis for the validity of certain features on the identified results in order to understand the rationale behind the model’s decisions and whether the decisions it makes are reliable. Improving the interpretability and reliability of the model is the core problem that needs to be addressed by clinically oriented algorithms for arrhythmia identification.

In this paper, a T-GRU fusion model is designed based on ECG time-frequency domain features and GRU networks. In this study, the gate recurrent unit (GRU) network model processes the time-domain features of the ECG signal, obtains the frequency-domain features of the ECG signal using the discrete FT, analyzes the discrete frequency-domain features through the decision tree, and finally weighs the fusion of the time-frequency domain feature output and gives the contribution of the time-frequency domain features of the fusion model to the results. The main areas of work in this study include the following:

1. Using the prior knowledge of the frequency domain and time domain of ECG data, the fusion algorithm is used to normalize the GRU model parameters and reduce the weight of its resultant output to improve the reliability of the fusion model

2. Decision tree probabilistic analysis of frequency domain features is introduced to discover the validity of low-frequency band features, and signal acquisition devices focusing on low-frequency bands can uncover more useful disease information

3. An incremental algorithm is designed to solve the problem of random selection of decision tree model band attribute nodes, and the algorithm improves the performance of the decision tree and fusion model

The remainder of the paper is organized as follows: Section 2 provides an overview of the T-GRU fusion model. Section 3 presents the experiments and results. Section 4 discusses the experimental results. Section 5 concludes the study.

2. Related Work

Remote wearable monitoring devices enable continuous monitoring of cardiac activity, enabling better medical care for patients with cyclical dirty diseases. These devices record a large amount of raw electrocardiogram (ECG, electrocardiogram) data, which provides the data base for classification and identification using deep learning techniques.

Currently, deep learning techniques have achieved high recognition results for arrhythmia recognition identification. Several works use convolutional neural networks to detect abnormal ECG signals. Zubair et al. [9] introduced a convolutional neural network based ECG beat classification system. By using a small and patient-specific training data, the classification system effectively classifies ECG signals into five categories. Acharya et al. [10] developed a 9-layer deep convolutional neural network that can automatically identify five different types of heartbeats in ECG signals. Kiranyaz et al. [11] used a one-dimensional convolutional neural network for classification of ECG signals. Hannun et al. [12] developed a deep neural network which consists of 33 convolutional layers followed by a linear output layer to form a softmax.

A few works used recurrent neural network (RNN) models for the classification of heartbeats. Based on morphological information and temporal information, Wang et al. [13] applied a single RNN for automatic feature learning and classification. Zhang et al. [14] proposed a patient-specific ECG classification algorithm based on recurrent neural networks and density clustering techniques. Hochreiter et al. [15] proposed a long-time short-time memory (LSTM) recurrent neural network model that can effectively alleviate the long-distance dependence on RNNs.

However, deep learning methods map discrete category data for each domain into a representation suitable for neural network input, using deep information mining to automatically extract abstract features, and such abstract data features make it difficult for doctors to understand the basis for the model’s classification.

But in reality, the model itself also implies knowledge, and doctors are more concerned with what the model learns from the data to produce decisions. If a model is completely uninterpretable, the application and deployment of the technology in the field of ECG identification will be limited by the inability to provide more reliable information.

Leveraging existing a priori knowledge of arrhythmias can improve model performance and the reliability of results. The local features of heartbeats are matrixed to generate global features [16], multilevel (beat, rhythm, and frequency level) domain knowledge features [17], and visual attention weights to improve model performance and interpretability. Gradient boosting trees are constructed to extract knowledge of cardiac behavior from DNNs to learn interpretable models and strong prediction rules [18]. The use of RNN to encode time variations in the 12-lead ECG signal sent to the attention module for advanced feature representation can be used for reliable diagnosis [19]. However, the main difference of this work is that the model has a high precision performance while providing a perceptually easy to understand contribution of frequency domain features from an energy point of view.

Deep learning-based ECG diagnostic algorithms can identify and determine arrhythmic events more effectively. However, deep learning techniques learn patterns and features of data from large amounts of data to represent output correlations rather than causal relationships. This causal uncertainty is key to the need for refinement of deep learning techniques, i.e., how to achieve effective classification recognition of ECGs, for reasons yet to be explored. To address
the problem of arrhythmia recognition, it is necessary to
explore a classification method that improves the credibility
of deep learning models.

3. Materials and Method

3.1. Dataset. The MIT-BIH arrhythmia database is recog-
nised as the definitive database of ECG heartbeat classi-
cfication algorithms, and each record includes one-half hour
segment of an ambulatory ECG with a 2-lead sampling rate
of 360 Hz, for a total of approximately 650,000 sampling
points. In total, there were over 109,000 marked beats from
15 different heartbeat categories, all marked by two or more
cardiologists. In this paper, nonredundant 2-lead ECG sig-
nals are used to train and test our method.

3.2. Preprocessing

3.2.1. Denoising. The discrete wavelet transform (DWT) [20]
is used to denoise the original data. The WT is a time-
frequency transformation method that analyzes the relation-
ship between signals by varying the data on different scales.
The usual discrete wavelet transform is:

\[
(W_{\psi}f)(a, b) = \langle f, \psi_{a,b} \rangle = \int_{-\infty}^{\infty} f(x) \psi(a^{-1} x - nb) \, dx.
\]  

Depending on the selection of the scale function, wavelet
transforms at different scales can be obtained, with the scale
transform being:

\[
\varphi_2(x) = 2 \varphi(2 \cdot x).
\]

The denoising results are shown in Figure 1, (a) the orig-
nal signal and (b) the denoised signal.

As can be seen from the diagram, the method not only stops the noise from interfering but also effectively separates
the signal from the noise.

Figure 1: Comparison of denoising results.

3.2.2. ECG Beat Segmentation. Excellent current R-peak
detection algorithms have achieved over 99% positive pre-
dictability and sensitivity [21–28], and here, we have used
the classical Pan-Tompkins algorithm to determine the R
position, as in Figure 2. The R-peak reference point is taken
as a heartbeat of about 0.3 s ahead and about 0.4 s behind,
about 250 points. An example of a partial public heartbeat
category after splitting is shown in Figure 3. (a) is normal
beat, (b) is premature or ectopic supraventricular beat, (c)
is ventricular escape beat, and (d) is fusion of ventricular
and normal beat.

A specific classification developed by the Association
for the Advancement of Medical Devices (AAMI) speci-
fies that the 15 ECG waveforms in the MIT-BIH database can
be classified into five categories: N (normal or bundle
branch conduction block), S (supraventricular ectopic
beats), V (ventricular ectopic beats), F (fusion beats), and
Q (unassigned beats). Similarly to [29], the Q class was
discarded because it has little representation in the data-
based. Table 1 shows the four categories of central beat data
considered.

Figure 2: R-peak detection position.

\[
\begin{align*}
\text{Original} & \quad \text{R-Wave} \\
\text{Original} & \quad \text{R-Wave} \\
\text{Original} & \quad \text{R-Wave} \\
\text{Original} & \quad \text{R-Wave}
\end{align*}
\]
3.3. Frequency Domain Feature Extraction. The commonly used time-frequency domain conversion methods are FT, continuous wavelet transform (CWT), and Hilbert–Huang transform (HHT). Among them, HHT lacks strict physical meaning and mathematical support. Differences in the choice of CWT base functions may cause inconsistencies in the analysis results. The FT converts a time-domain signal into an easily analyzed frequency domain signal, i.e., a signal spectrum, which can be used to accurately calculate the composite modulus vector at each frequency. In addition, FT

![Figure 3: Diagram of some types of heartbeat.](image)

| MIT database heartbeat comment information | Total |
|-------------------------------------------|-------|
| Normal beat                               |       |
| Left bundle branch block beat             |       |
| Right bundle branch block beat            |       |
| Nodal (junctional) escape beat            |       |
| Atrial escape beat                        |       |
| Aberrated atrial premature beat           |       |
| Nodal (junctional) premature beat         |       |
| Atrial escape beat                        |       |
| Premature or ectopic supraventricular beat|       |
| Premature ventricular contraction         |       |
| Premature ventricular escape              |       |
| S, Atrial prematurity escape              |       |
| V, Premature ventricular contraction      |       |
| Ventricular escape beat                   |       |
| F, Fusion of ventricular and normal beat   |       |
| Paced beat                                |       |
| Q, Unclassifiable beat                    |       |
| Fusion of paced and normal beat           |       |
| Unclassifiable beat                       |       |

Table 1: Five types of heartbeat data.
keeps the total amount of information constant during the transformation to the greatest extent possible.

The frequency domain feature segmentation depends on the QRS time-domain feature distribution interval. The QRS wave reflects the electrical behavior of the heart during ventricular contraction and has a large energy share. The discrete Fourier transform (DFT) was used to obtain the characteristics of each subband of the heartbeat. As in Figure 4, where (a) P-wave band, (b) QRS-wave band, and (c) T-wave band.

3.4. Methods

3.4.1. Problem Description. The identification of arrhythmias can be translated into a multiclass task that can be structured using a softmax regression model as the last layer of the T-GRU (Figure 5) fusion model. The ECG time-domain training set \( R_1 \) is used as an input to the GRU model input layer and is output as the probability of each class of heartbeat. \( R_1 = \{ (x^{(1)}, y^{(1)}), \ldots, (x^{(i)}, y^{(i)}), \ldots, (x^{(n)}, y^{(n)}) \} \), \( x^{(i)} \) is a time-domain signal sample, and \( y^{(i)} \in \{0,1,2,3\} \) is the class label of \( x^{(i)} \). The discrete Fourier transform is used to obtain the frequency domain training set \( R_2 \) as input to the decision tree and output as the corresponding label. Finally, the time-frequency domain output results are standardized and output through the fusion network model. Details are given in a subsequent section.

3.4.2. GRU Model. GRU overcomes RNN’s inability to handle long-range dependencies well, maintaining the effect of LSTM while making the structure simpler [30]. GRU is widely used in various time-domain scenarios, such as speech recognition and music and audio analysis [31], and is a good choice for ECG time-domain data classification.

As shown in Figure 6, the GRU model mainly consists of an input layer, a GRU network layer, and two fully connected layers. The input layer is the bottom component of the GRU model whose output is sent to the GRU network layer and is responsible for the preprocessing of the raw ECG time-domain data.

The GRU network layer consists of several GRU units (Figure 7) and is responsible for calculating the input hidden state as the first fully connected layer input. Each GRU unit consists of an update gate and a reset gate, with update gate \( Z \) deciding whether to update the new hidden layer state \( \tilde{h} \) to the hidden layer state \( h \) and reset gate \( r \) deciding whether the previous hidden layer state is forgotten.

\[
\begin{align*}
z_t &= \sigma(W_z \cdot [h_{t-1}, x_t]), \\
r_t &= \sigma(W_r \cdot [h_{t-1}, x_t]), \\
h_t &= \tanh(w_h \cdot [r_t \odot h_{t-1}, x_t]),
\end{align*}
\]

Figure 4: Example of subband segmentation.
\[ \tilde{h}_t = (1 - z_t) \ast h_{t-1} + z_t \ast \tilde{h}_t. \]

\[ S_i = \frac{e^{V_i}}{\sum_i e^{V_i}}. \]

\[ i \] represents the category index, \( V_i \) is the output of the classifier's previous output unit, and \( S_i \) represents the ratio of the index of the current element to the sum of all element indices.

### 3.4.3. Incremental Decision Tree Model

The interpretative nature of tree classifiers is an important advantage over neural networks [32], which is suitable for capturing interactive information about discrete frequency domain features.
The decision tree model uses the CART algorithm. The “Gini index” is utilized to select the frequency complex mode vector attributes, and the Gini index classification for each leaf node in the tree is defined as follows:

\[
Gini \ index = 1 - \sum_{i} \left( \frac{n_i}{N} \right)^2,
\]

where \(N\) represents the total number of frequency domain samples considered for that node and \(n_i\) represents the frequency domain signal label.

Pruning uses a cost-complexity-based approach with a loss function defined as follows:

\[
C_{\alpha}(T) = C(T) + \alpha |T|.
\]

\(T\) is an arbitrary subtree, \(C(T)\) arbitrarily measures the fit of the training data, \(|T|\) measures the complexity of the tree, and \(\alpha\) weighs the fit of the data against the complexity of the tree. \(\alpha\) is taken from 0 to positive infinity to obtain the optimal subtree \(T(\alpha)\) after pruning, and the output result is \(D_i(1 \leq i \leq 4)\).

During the training of the decision tree, the criterion value of the frequency band attribute judgment is close to the critical value, and the node problem of splitting the random selection attribute occurs. Using an incremental algorithm (Algorithm 1), the decision tree training process eliminates junk samples to improve the generalization ability of the model, which is \(\vartheta\).

The sample data set was divided into ten equal parts, leaving 10% as the test set. For the remainder, an incremental algorithm was used, taking 10% of the samples at a time as the training set (9 times in total) and 80% as the validation set. The validation process is recorded as \(\Theta\). With constraint \(f\), calculate the Gini index for all frequency attributes and then find the attribute with the largest Gini index to partition.
all data. This process is repeated for all partitions to obtain the spanning tree $T_k$ to carry out the process $\Theta$ with $\theta$ and finally to generate the maximum subtree $T_0$.

3.4.4. Converged Network Model. As shown in Figure 8, the fusion network model is based on the CNN model with the aim of establishing a weight adaptive mechanism. The traditional approach to model fusion is linear weighting of fixed parameters, and in practice, the selection of parameters usually relies on lifting the global results. The CNN local sense field advantage facilitates learning local to global weighting information and adjusting the weighting dynamically. The CNN input is the weighting parameter $W_i^c$ after regularization of the GRU network model parameters.

The CNN network mainly consists of the weight input layer, Conv1D one-dimensional convolution layer, MaxPool1D one-dimensional pooling layer, GAPool1D global average one-dimensional pooling layer, dropout random inactivation layer, dense full connection layer, and softmax layer, where the first one-dimensional convolutional layer extracts the features of the weight $W_i^c$, the one-dimensional pooling layer convolutional kernel is $2 \times 2$, the step is 2, and the padding is “SAME.” Finally, the output of the CNN network is $W_i (1 \leq i \leq 2)$.

The goal of the fusion algorithm is to maximize the contribution of ECG frequency domain features to the weight of the fusion model results. The network weights of the GRU model are first attenuated using L2 regularization to reduce the overfitting of the model to some extent. The GRU model uses a cross-entropy loss function.

$$L_i = -s_{ij} \log \sum_{j=1}^{k} e^{f_j}.$$  

The linear scoring function corresponds to the correct category of $s_{ij}$,

$$C = L_i + \frac{\lambda}{2n} \sum_{w} w^2 + 0.001 \ast W_1,$$  

where $L_i$ represents GRU’s cost function, $(\lambda/2n)\sum_{w} w^2$ is the L2 regularization term, and $\lambda$ is the regular term coefficient ($0 < \lambda \leq 0.1$).

The output of the GRU model after L2 parameter regularization is softmax($\sum_i W_i h_i$). Moreover, the decision tree model output is $D_j$.

The CNN network learning GRU global weights output $W_i$. The decision tree model takes $W_i$ with the largest weight as $W_2$. Then, the GRU model weight is $W_1$. Finally, the final result is output by the softmax function, and the fusion algorithm is as follows.

4. Experiments and Results

4.1. Experimental Data Division. In this paper, N, S, V, and F heartbeats were used as experimental data. The partitioned heartbeat data are randomly disordered. The ECG time-domain part is used as 80% as the training set, 10% as the validation set, and 10% as the test set. The frequency domain section is divided into ten equal portions of the sample data set, and the incremental algorithm is used.

4.2. Evaluation Indicators. The models were evaluated using sensitivity (Sen), specificity (Spe), precision (Pre), and accuracy (Acc). The formulas for calculating the four evaluation indicators are as follows:

$$\text{Sen} = \frac{TP}{TP + FN},$$

$$\text{Spe} = \frac{TN}{TN + FP},$$

$$\text{Pre} = \frac{TP}{TP + FP},$$

$$\text{Acc} = \frac{TP + TN}{TP + FN + TN + FP},$$

where $TP$ (true positive) is the number of samples that predicted the abnormal signal as abnormal, $TN$ (true negative) is the number of samples that predicted the normal signal as normal, $FP$ (false positive) is the number of samples that predicted the normal signal as abnormal, and $FN$ (false negative) is the number of samples that predicted the abnormal signal as normal. Acc indicates the overall classification accuracy of the overall model; Sen indicates the proportion of anomalous signals classified correctly, which measures the model’s ability to identify anomalous signals; Spe indicates the proportion of normal signals classified correctly, which measures the classifier’s ability to identify normal signals; and Pre indicates the proportion of signals classified as anomalous that are actually labeled as anomalous.

4.3. Experiment 1. To verify the validity of the GRU model for time-domain signal detection, the segmented time-domain heartbeat sequence data were entered into the GRU network model (Figure 9).

After GRU network layer learning, the results were input to a fully connected softmax layer. To obtain better classification results, the network is constrained using the L2 regularization method. After 30 epochs, the GRU network converges, and the accuracy stabilizes as shown in Figure 9.

For cell effects, change the initial value of batch size and calculate the effect of different cells on the accuracy in 30
epochs. Table 2 shows that the best accuracy is 97.52% when cell is 64.

For batch size effects, as shown in Table 3, the best accuracy obtained was 97.36 for batch size = 128 for an epoch of 30 and cell of 64.

Under optimal parameters, the Acc is 97.53%, the Sen is 95.3%, the Spe is 94.76%, and the Pre is 96.31%. The results show that the model is useful for automatic auxiliary analysis of ECG time-domain signals.

### Table 2: Classification accuracy of different cell.

| Cell | 8   | 16  | 32  | 64  | 128 | 256 |
|------|-----|-----|-----|-----|-----|-----|
| Acc (%) | 96.13 | 96.56 | 97.21 | 97.52 | 97.31 | 97.26 |

### Table 3: Classification accuracy of different batch sizes.

| Batch_size | 16  | 32  | 64  | 128 | 256 |
|------------|-----|-----|-----|-----|-----|
| Acc (%) | 83.1 | 85.21 | 94.32 | 97.36 | 92.23 |

### Table 4: Classification performance evaluation of different frequency bands.

| Frequency band | Sen (%) | Spe (%) | Pre (%) | Acc (%) |
|----------------|---------|---------|---------|---------|
| 5 | 81.23 | 76.02 | 85.37 | 92.23 |
| 25 | 90.11 | 82.73 | 89.61 | 95.19 |
| 45 | 93.23 | 91.02 | 91.17 | 95.21 |
| 65 | 93.03 | 91.46 | 91.35 | 95.25 |
| 85 | 93.47 | 91.77 | 91.37 | 95.26 |
| 105 | 93.61 | 91.75 | 91.42 | 95.31 |
| 125 | 93.63 | 92.15 | 91.39 | 95.34 |

### Table 5: Influence of frequency domain feature segmentation on classification performance.

| Segmentation | Sen (%) | Spe (%) | Pre (%) | Acc (%) |
|--------------|---------|---------|---------|---------|
| With | 93.68 | 92.23 | 91.65 | 95.41 |
| Without | 93.59 | 92.17 | 91.60 | 95.32 |

### Table 6: The effect of incremental algorithm on classification performance.

| Algorithm   | Sen (%) | Spe (%) | Pre (%) | Acc (%) |
|-------------|---------|---------|---------|---------|
| Incremental | 95.03 | 94.43 | 93.07 | 96.68 |
| Without incremental | 93.67 | 92.19 | 91.71 | 95.43 |

### Table 7: Overall classification performance.

| Algorithm | Sen (%) | Spe (%) | Pre (%) | Acc (%) |
|-----------|---------|---------|---------|---------|
| Tree      | 95.07 | 94.46 | 93.05 | 96.67 |
| GRU       | 95.9  | 94.72 | 96.33 | 97.52 |
| T-GRU     | 96.85 | 98.81 | 96.73 | 98.31 |
The frequency bands on the results of the decision tree model is verified without the frequency domain feature segmentation condition. The first five frequency bands are taken for the first time, and then, 20 additional frequency domain bands in sequence are used as input to the decision tree model. The DFT has conjugate symmetry, and the first 125 frequency bands are taken. Outputting their results as in Table 4, under the condition of no frequency domain data segmentation, the accuracy of the first 45 bands differs from the first 125 bands by 0.13%, indicating that the lower band features were more important to the results.

To verify the performance of frequency domain data segmentation in the decision tree model, the classification results of frequency domain features without data segmentation are compared with those with data segmentation (Table 5). The results show that the data segmentation improves the performance of the model; the frequency domain data processing process is better interpreted by exploring each subwavelength using the decision tree model.

On the basis of frequency domain features with data segmentation, the training process uses an incremental algorithm. Table 6 shows that the Acc is 96.68%, Sen is 95.03%, Spe is 94.43%, and Pre is 93.07%. The incremental algorithm further improves the performance of the model.

As shown in Table 4, under the condition of no frequency domain data segmentation, the accuracy of the first 45 bands differs from the first 125 bands by 0.13%, which indicates that the decision tree model gives classification results mainly based on the low frequency bands, and the classification results have a certain degree of confidence. In addition, in practical applications, especially with signal acquisition equipment, the focus on the low frequency band when extracting features in the frequency domain can uncover more useful information about the disease.

4.5. Experiment III. Under the incremental algorithm condition, the frequency domain data with segmented time-domain centroid sums are entered into the T-GRU fusion model. As shown in Table 7, the fusion model is significantly better than the single-domain, single-classifier model. And the sample weights $W_2$ interval for CNN learning is for 0.59-0.68.

5. Discussion

In this paper, a T-GRU fusion model is designed to address the problem of identifying and diagnosing cardiac arrhythmias. The learning is based on ECG time-domain features and frequency domain features to improve the credibility of the deep learning model.
fusion model results than the time-domain features, and the fusion model has some credibility.

The fusion model maintains a certain level of confidence while also taking into account the classification performance. Table 8 gives the average evaluation results obtained using the T-GRU fusion model on the MIT-BIH dataset in comparison to other recent methods.

The T-GRU fusion model designed in this paper is, on average, just less accurate than Emina’s method when the AAMI criteria are not used. Emina et al. used the discrete wavelet transform (DWT) to extract the wavelet coefficient features of the obtained frequency band representation distribution and finally used a random forest (RF) classifier in the diagnosis of ECG heartbeat signal classification. The AAMI standard specifies five main categories with a total of 15 different heartbeats. Emina’s method of classifying arrhythmias was selected from only five; they are normal beat, left bundle branch block beat, right bundle branch block beat, atrial premature contraction beat, and premature ventricular contractions beat. This paper uses the AAMI criteria to actually select a total of 12 different heartbeats in four categories, N, S, V, and F. The average classification accuracy is just 1.02% lower.

The average accuracy of the method proposed in this paper is only 0.06% lower than WeiZhao’s method when using the AAMI standard conditions. WeiZhao et al. Two leading heartbeat segments of length 2 s were generated on the filtered signal and classified by an adaptive ResNet model. The method has some advantages in terms of performance in classifying arrhythmias on ECG signals, and the lack of a basis for model decisions in an entirely DNN-based approach limits physicians’ trust in such methods.

The fusion model provides a degree of confidence while maintaining high performance. However, frequency domain features have not yet been used extensively in clinical diagnosis, frequency domain features are less linked to medical knowledge, and a large amount of data is needed to determine their discriminatory criteria.

6. Conclusions

To address the problem of arrhythmia recognition, this paper focuses on exploring classification on methods to improve the credibility of deep learning models. A decision tree measured by information entropy as a metric is introduced to analyze the contribution of each frequency band feature to the prediction results. Fusion network CNN is used to assess the contribution of the data feature variables to the fusion results of the model. The experimental results show that the regularized GRU network parameters, particularly frequency domain features, contribute more to the results of the T-GRU fusion model than the time-domain features. The fusion model has a certain degree of credibility, which is of high reliability and clinical utility when applied to ECG automatic aid analysis.

Currently, frequency domain features are less associated with medical knowledge. To further enhance the trustworthiness of deep learning models, future research will explore medical linkage of frequency domain features or direct construction of trustworthy deep learning methods based on ECG time-domain features.

Data Availability

The data used to support the findings of this study are included in the article. Further data can be requested from the corresponding author.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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References

[1] M. K. Das and S. Ari, “ECG beats classification using mixture of features,” International Scholarly Research Notices, vol. 2014, Article ID 178436, 12 pages, 2014.

[2] F. Yang, J. du, J. Lang et al., “Missing value estimation methods research for arrhythmia classification using the modified kernel Difference-Weighted KNN algorithms,” BioMed Research International, vol. 2020, Article ID 7141725, 9 pages, 2020.

[3] S. Raj and K. C. Ray, “ECG signal analysis using DCT-based DOST and PSO optimized SVM,” IEEE Transactions on Instrumentation & Measurement, vol. 66, no. 3, pp. 470–478, 2017.

[4] D. G. Wilson, G. Leventianni, C. Barr, and J. M. Morgan, “ECG predictors of T wave oversensing in subcutaneous implantable cardioverter defibrillators,” International Journal of Cardiology, vol. 220, pp. 27–231, 2016.

[5] S. H. El-Khaff and M. A. El-Brawany, “Artificial neural network-based automated ECG signal classifier,” Isrn Biomedical Engineering, vol. 2013, Article ID 201113, 6 pages, 2013.

[6] Y. Dai, G. Wang, and K. C. Li, “Conceptual alignment deep neural networks,” Journal of Intelligent & Fuzzy Systems Applications in Engineering & Technology, vol. 34, no. 3, pp. 1631–1642, 2017.

[7] J. Gao, H. Zhang, P. Lu, and Z. Wang. “An effective LSTM recurrent network to detect arrhythmia on imbalanced ECG dataset,” Journal of Healthcare Engineering, vol. 2019, Article ID 6320651, 10 pages, 2019.

[8] Y. Li, Y. Pang, J. Wang, and X. Li, “Patient-specific ECG classification by deeper CNN from generic to dedicated,” Neurocomputing, vol. 314, pp. 336–346, 2018.

[9] M. Zubair, J. Kim, and C. Yoon, “An automated ECG beat classification system using convolutional neural networks,” in 2016 6th International Conference on IT Convergence and Security (ICITCS), pp. 1–5, Prague, Czech Republic, 2016.
[10] U. R. Acharya, S. L. Oh, Y. Hagiwara et al., “A deep convolutional neural network model to classify heartbeats,” Computers in Biology and Medicine, vol. 89, pp. 389–396, 2017.

[11] S. Kiranyaz, T. Ince, and M. Gabbouj, “Real-time patient-specific ECG classification by 1-D convolutional neural networks,” IEEE Transactions on Biomedical Engineering, vol. 63, no. 3, pp. 664–675, 2016.

[12] A. Y. Hannun, P. Rajpurkar, M. Haghpanahi et al., “Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network,” Nature Medicine, vol. 25, no. 1, pp. 65–69, 2019.

[13] G. Wang, C. Zhang, Y. Liu et al., “A global and updatable ECG beat classification system based on recurrent neural networks and active learning,” Information Sciences, vol. 501, pp. 523–542, 2019.

[14] C. Zhang, G. Wang, J. Zhao, P. Gao, J. Lin, and H. Yang, “Patient-specific ECG classification based on recurrent neural networks and clustering technique,” in 2017 13th IASTED International Conference on Biomedical Engineering (BioMed), pp. 63–67, Innsbruck, Austria, 2017.

[15] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[16] R. Li, X. Zhang, H. Dai, B. Zhou, and Z. Wang, “Interpretability analysis of heartbeat classification based on heartbeat activity’s global sequence features and BiLSTM-attention neural network,” IEEE Access, vol. 7, pp. 109870–109883, 2019.

[17] S. Hong, C. Xiao, T. Ma, H. Li, and J. Sun, “MINA: multilevel knowledge-guided attention for modeling electrocardiography signals,” in Twenty-Eighth International Joint Conference on Artificial Intelligence [IJCAI-19], pp. 5888–5894, Macao, China, 2019.

[18] S. Hong, Y. Zhou, M. Wu et al., “Combining deep neural networks and engineered features for cardiac arrhythmia detection from ECG recordings,” Physiological Measurement, vol. 40, no. 5, article 054009, 2019.

[19] J. Zhang, A. Liu, M. Gao, X. Chen, X. Zhang, and X. Chen, “ECG-based multi-class arrhythmia detection using spatio-temporal attention- based convolutional recurrent neural network,” Artificial Intelligence in Medicine, vol. 106, article 101856, 2020.

[20] P. Singh and G. Pradhan, “Significance of non-local means estimation in DWT based ECG signal denoising,” in 2018 5th International Conference on Signal Processing and Integrated Networks (SPIN), pp. 18–22, Noida, India, 2018.

[21] V. Gupta and M. Mittal, “QRS complex detection using STFT, chaos analysis, and PCA in standard and real-time ECG databases,” Journal of the Institution of Engineers, vol. 100, no. 5, article 398, pp. 489–497, 2019.

[22] V. Gupta and M. Mittal, “R-peak detection in ECG signal using Yule–Walker and principal component analysis,” IETE Journal of Research, pp. 1–14, 2019.

[23] V. Gupta, M. Mittal, and V. Mittal, “R-peak detection based chaos analysis of ECG signal,” Analog Integrated Circuits and Signal Processing, vol. 102, no. 3, article 1556, pp. 479–490, 2020.

[24] V. Gupta, M. Mittal, and V. Mittal, “A novel method of cardiac arrhythmia detection in electrocardiogram signal,” International Journal of Medical Engineering and Informatics, vol. 12, no. 5, pp. 489–499, 2020.

[25] V. Gupta, M. Mittal, and V. Mittal, “R-peak detection using chaos analysis in standard and real time ECG databases,” Innovation and Research in BioMedical Engineering, vol. 40, no. 6, pp. 341–354, 2019.

[26] V. Gupta, M. Mittal, and V. Mittal, “Chaos theory: an emerging tool for arrhythmia detection,” Sensing and Imaging An International Journal, vol. 21, no. 1, p. 21, 2020.

[27] V. Gupta, M. Mittal, and V. Mittal, “An efficient low computational cost method of R-peak detection,” Wireless Personal Communications, vol. 118, no. 1, article 8017, pp. 359–381, 2021.

[28] V. Gupta and M. Mittal, “Arrhythmia detection in ECG signal using fractional wavelet transform with principal component analysis,” Journal of The Institution of Engineers (India) Series B, vol. 101, no. 5, pp. 451–461, 2017.

[29] E. Luz, L. H. C. Merschmann, D. Menotti, and G. J. P. Moreira, “Evaluating a hierarchical approach for heartbeat classification from ECG,” International Journal of Bioinformatics Research and Applications, vol. 13, no. 2, pp. 146–160, 2017.

[30] S. Xu, J. Li, K. Liu, and L. Wu, “A parallel GRU recurrent network model and its application to multi-channel time-varying signal classification,” IEEE Access, vol. 7, pp. 118739–118748, 2019.

[31] H. M. Lynn, S. B. Pan, and P. Kim, “A Deep Bidirectional GRU Network Model for Biometric Electrocardiogram Classification Based on Recurrent Neural Networks,” IEEE Access, vol. 7, pp. 145395–145405, 2019.

[32] S. Lubnegg, G. Erión, H. Chen et al., “From local explanations to global understanding with explainable AI for trees,” Nature Machine Intelligence, vol. 2, no. 1, pp. 56–67, 2020.

[33] J. Huang, B. Chen, B. Yao, and W. He, “ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network,” IEEE Access, vol. 7, pp. 92871–92880, 2019.

[34] W. Zhao, J. Hu, D. Jia et al., “Deep learning based patient-specific classification of arrhythmia on ECG signal,” in 2019 41st Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pp. 1500–1503, Berlin, Germany, 2019.

[35] J. Liu, S. Song, G. Sun, and Y. Fu, “Classification of ECG arrhythmia using CNN, SVM and LDA,” Artificial Intelligence and Security., pp. 191–201, 2019.

[36] R. Zhou, X. Li, B. Yong et al., “Arrhythmia recognition and classification through deep learning-based approach,” International Journal of Computationalerce and Engineering, vol. 19, no. 4, pp. 506–517, 2019.

[37] O. Yildirim, M. Talo, B. Ay, U. B. Baloglu, G. Aydin, and U. R. Acharya, “Automated detection of diabetic subject using pre-trained 2D-CNN models with frequency spectrum images extracted from heart rate signals,” Computers in Biology and Medicine, vol. 113, article 103387, 2019.

[38] M. M. A. Gad, “Feature extraction of electrocardiogram signals using discrete sinc transform,” in 2016 9th Biomedical Engineering International Conference (BMEICON), pp. 1–4, Luang Prabang, Laos, 2016.

[39] T. Li and M. Zhou, “ECG classification using wavelet packet entropy and random forests,” Entropy, vol. 18, no. 8, article e18080285, p. 285, 2016.

[40] S. Alickovic and A. Subasi, “Medical decision support system for diagnosis of heart arrhythmia using DWT and random forests classifier,” Journal of Medical Systems, vol. 40, no. 4, p. 40, 2016.

[41] S. Y. En and N. Ozkurt, “ECG arrhythmia classification by using convolutional neural network and spectrogram,” in Computational and Mathematical Methods in Medicine.
2019 Innovations in Intelligent Systems and Applications Conference (ASYU), pp. 1–6, Izmir, Turkey, 2019.

[42] Q. Qin, J. Li, and C. Liu, “Multi-classification of cardiac diseases utilizing wavelet thresholding and support vector machine,” in International Conference on Frontiers of Biological Sciences and Engineering (FBSE 2018), Chongqing, Peoples Republic of China, 2019.

[43] A. Nasim, A. Shrollini, M. Morettini, and L. Burattini, “Extended segmented beat modulation method for cardiac beat classification and electrocardiogram denoising,” Electronics, vol. 9, no. 7, p. 1178, 2020.