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Application of ECG signal processing and classification based on CNN in wearable devices

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Abstract. To address the issue of ECG signals being susceptible to internal and external noise interference during the acquisition process, in this paper, a novel ECG signal processing and classification method based on convolutional neural network (CNN) is proposed, which combines advanced Wavelet transform technology to achieve high precision classification of real-time ECG signals. Specifically, the method first uses Wavelet transform to preprocess and de-noise ECG signals to improve signal quality. Then, a customized CNN model is used to extract and classify the preprocessed ECG signals. The CNN model can be trained to accurately predict the type of ECG signal. The innovation of this paper lies in combining the highly efficient denoising capability of Wavelet transform with the powerful feature extraction capability of CNN algorithm to realize the high-precision classification of ECG signals. This approach not only improves the accuracy and reliability of ECG signal monitoring, but also opens the possibility of more effective health monitoring and disease prevention. The experimental results demonstrate significant improvements in the clarity and classification accuracy of the preprocessed ECG signals, with the trained CNN model achieving a 99% accuracy rate in predicting ECG signal types. This advancement not only enhances the accuracy and reliability of ECG signal monitoring by wearable devices but also provides possibilities for more effective health monitoring and disease prevention.

Keywords: CNN; ECG; signal processing; health monitoring.

1. Introduction

This paper introduces an advanced technology named "Application of ECG signal processing and classification based on CNN in wearable devices" to achieve more effective health monitoring and disease prevention. The first issue arises from the fact that ECG signals, while being collected, are often contaminated by various sources of noise, both internal such as muscle activity and external like electromagnetic interference, which can lead to inaccurate health assessments. The second challenge is the necessity for a system that can promptly and reliably categorize heartbeats into normal (N), atrial premature beat (A), ventricular premature beat (V), left bundle branch block (L), and right bundle branch block (R) categories to facilitate timely medical interventions.

To tackle these problems, this paper presents an innovative method for processing and classifying ECG signals using convolutional neural networks (CNN) to improve the accuracy of health monitoring and promote timely intervention. By combining advanced signal processing techniques with deep learning, our approach effectively addresses noise pollution common in ECG data and provides fast, reliable representation of five different heartbeat categories. The implementation of this approach is critical to the development of wearable health monitoring devices, which can give individuals a more detailed picture of their heart rate health and the ability to adjust their health management strategies in a timely manner.

2. Model Preparation

The process outlined in this paper for ECG signal analysis integrates wavelet transform denoising and CNN-based classification to accurately identify and categorize heartbeats, as detailed in Fig.1.

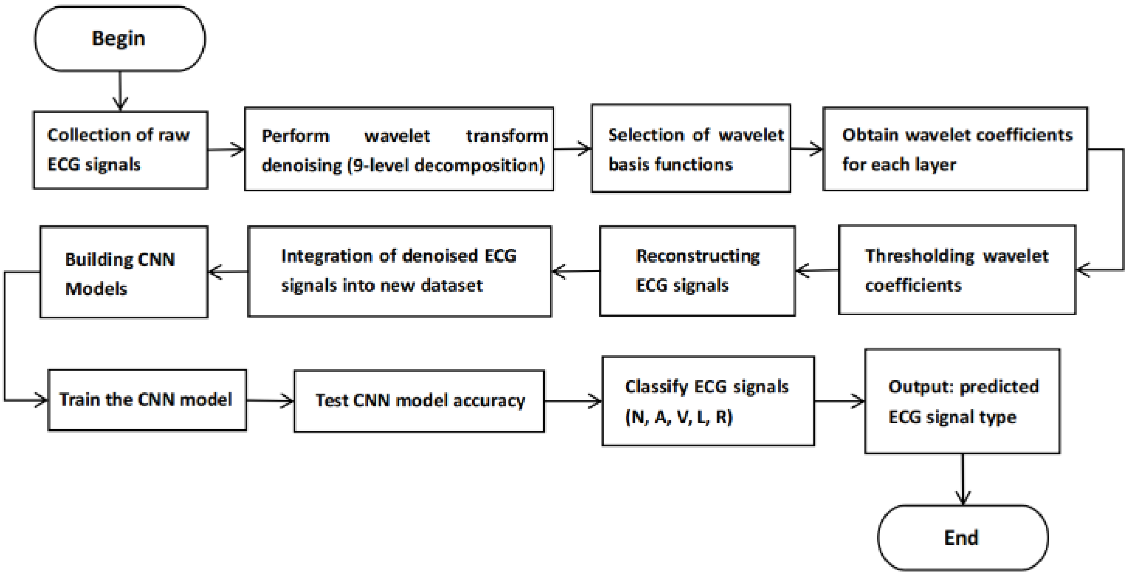


Figure 1. Flowchart of overall proposed methodology

2.1. The choice of treatment method Classification and Recognition of ECG Signals

ECG signals are usually very weak and easily interfered by various factors, such as Electromagnetic Interference (EMI), Environmental Vibrations, Muscle and Motion Artifacts, during the acquisition process. There is a wide variety of noise in ECG signals, the first step in the classification and recognition of ECG is to pre-process of the signals. In this step, we employ wavelet transform as our primary preprocessing method, which will be detailed extensively in the subsequent sections. This approach effectively filters out noise and enhances the signal-to-noise ratio, paving the way for accurate ECG signal classification and recognition. The rapid development of wavelet transform technology has given rise to a series of denoising techniques based on wavelet thresholding. This type of technique is based on the distribution of the frequency of the signal and noise on different scales, the signal is first wavelet transformed, then the wavelet coefficients of each layer are processed according to the threshold, and finally the signal is reconstructed to achieve denoising. Wavelet thresholding denoising technique has excellent processing effect for non-smooth signals and has significant superiority over traditional processing methods.

On top of pre-processing and feature extraction of ECG signals, deep learning is used for automatic classification and identification of ECG signals. Deep learning research is linked to neural networks. The convolutional neural network used in this paper is capable of extracting features of ECG signals and performing deep learning. In the study of ECG classification algorithms, the advantages of deep learning in processing large amounts of data were utilised, resulting in a significant improvement in the classification results.

2.2. Database of electrocardiographic signals

In this work, the MIT-BIH arrhythmia database is used [6]. The database is widely used, including all types of ECG signals, and provides experimental data for the automatic classification of ECG signals. These signals are initially in medical devices in hospitals, but with the development of technology, there are many wearable devices that can get these signals now and, in the future, [7]. Fig.2 shows the characteristic waveform of ECG signal. This waveform has several important interest points and segments, such as P, Q, R, S, T, PR segment and ST segment.

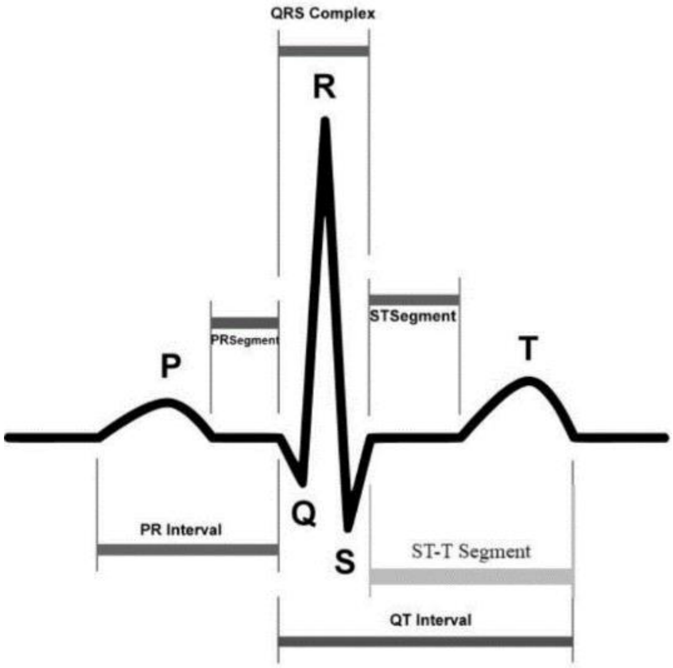


Figure 2. One-dimensional u-net single guide electrocardiogram signal characteristic waveform[8]

2.3. Signal preprocessing

Wavelet Transform (WT) can perform time-frequency transformation, which is the most ideal tool for analyzing signals in time domain as well as frequency domain. In this paper, the denoising method based on wavelet transform is adopted for the noisy ECG signal, which is divided into the following six steps. Fig.3 shows the process of denoising the original ECG signals.

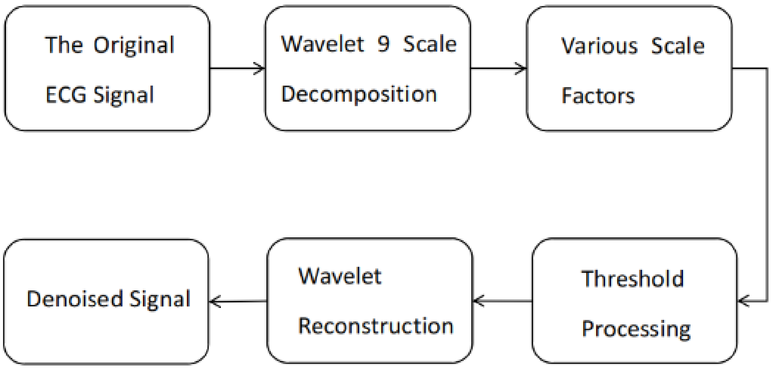


Figure 3. Denoising process for the original ECG signals

In the process of enhancing ECG signals for health monitoring with wearable devices, the initial step involves collecting the original ECG signals from a dataset. Due to the complex nature of ECG signals, which contain a mix of various features, the signals are then decomposed nine times using wavelet transform to better isolate and reduce noise. A wavelet basis function is selected at the outset, and the noisy ECG signal is decomposed at specific scales to obtain wavelet coefficients that represent the signal and noise. The next phase involves thresholding these coefficients; the larger amplitude coefficients, indicative of the useful signal, are retained, while the smaller amplitude coefficients, identified as noise, are either set to zero or modified using a threshold function. This process allows for the reconstruction of the ECG signal, yielding a preliminary dataset that is notably cleaner and more feature-defined. The final step is to collect the reconstructed ECG signals, which are now free of noise, and integrate them into a new dataset, thereby completing the entire noise reduction process and preparing the ECG signals for subsequent analysis and classification tasks. Fig.4 shows the process of discrete wavelet transform. Given a signal x [n], we first use special low-pass and high-pass filters to filter the signal to generate low-pass and high-pass subbands, which are called A1 and

D1. According to the Nyquist criterion, half of the samples are discarded after filtering. The filters usually have a small number of coefficients and have good computational performance. These filters also have the ability to reconstruct the subbands while eliminating any aliasing caused by down sampling. For the next level of decomposition, the low-pass sub-band A1 is iteratively filtered by the same technique to produce narrower sub-bands A2 and D2, and so on.

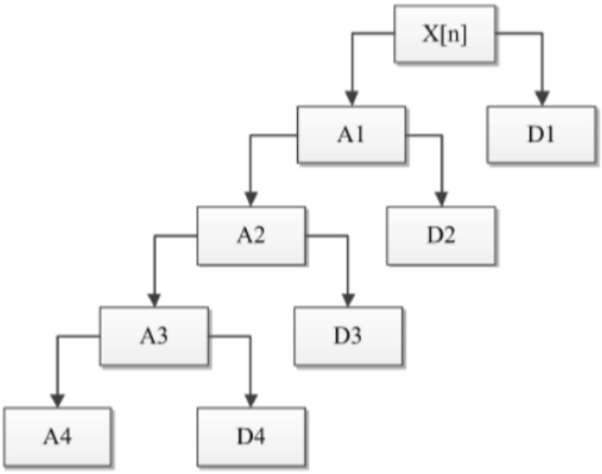


Figure 4. Decomposition of the coefficients at each scale of the signal

2.4. Signal denoising and filtering

Table 1 shows the frequency range of signal decomposition. According to the Nyquist criterion, half of the frequency samples are discarded each time for dichotomous processing. Since the sampling frequency of MIT-BIH ECG signal is 360 Hz, according to the Nyquist sampling theorem, the maximum frequency of the original ECG signal is below 180 Hz, so the maximum frequency of the D1 layer of signal decomposition is 180 Hz. After decomposing the original signal, it can be known that the energy of the detail components in the D1-D2 layer conforms to the high-frequency interference of the original signal. It can be seen that the D1-D2 layer is the main location of high frequency noise. Therefore, the detail components of the D1 and D2 layers need to be set to 0 to achieve the purpose of removal. Then, the wavelet coefficients of the D3-D9 layer obtained by signal decomposition are processed by soft threshold formula:

$$z_{\lambda} = \begin{cases} [sign(z)](|z| - \lambda) & |z| \geq \lambda \\ 0 & |z| \leq \lambda \end{cases} \tag{1}$$

Where z is the coefficient after wavelet transform, λ is the selected threshold. Finally, the inverse transform of the wavelet coefficients is performed to obtain the denoised signa

Table 1. Signal signal decomposition frequency range

Signal Decomposition	Frequency range
D1	90-180
D2	45-90
D3	22.5-45
D4	11.25-22.5
D5	5.625-11.25
D6	2.8125-5.625
D7	1.40625-2.8125
D8	0.703125-1.40625
D9	0-0.703125

2.5. Constructing a dataset for deep learning

Although there are already pre-processed ECG data, such data cannot be used for direct classification learning. Therefore, a data set compatible with the use of deep learning models must be constructed. Since only the network model is currently trained, the manual annotation provided by the MIT-BIH dataset is directly used to form a complete heartbeat. The data is a list of several heartbeats sliced out after preprocessing. The slice of the heartbeat needs to find the location of the QRS wave peak. The label is the ECG category corresponding to each heartbeat sample. The process of transformation is shown in Fig. 5 First, the heartbeat is intercepted from the ECG signal that meets the requirements as a sample, and then it is reordered and cut to form a data set that can be used for deep learning. In our experiment, the data set is divided into a training set and a test set, with a ratio of 7:3. And 30% of the training set is the validation set. The training set is used to train the parametric model, the test set is used to test the training effect after the training is completed, and the verification set is used to test the accuracy and error (loss function) in the model training.

Figure 5. Data set conversion process

By manipulating the original ECG signal, the wanted part of the ECG signal is preserved. Finally, the feature points of the signal are preserved, and the unwanted feature points are filtered out, making the image features clearer.

3. Experiment results

3.1. Noise reduction and filtering of raw ECG signals

The experiment starts with ECG filtering and denoising obtained from the data set. Fig. 6 shows the ECG signal before and after filtering and denoising.

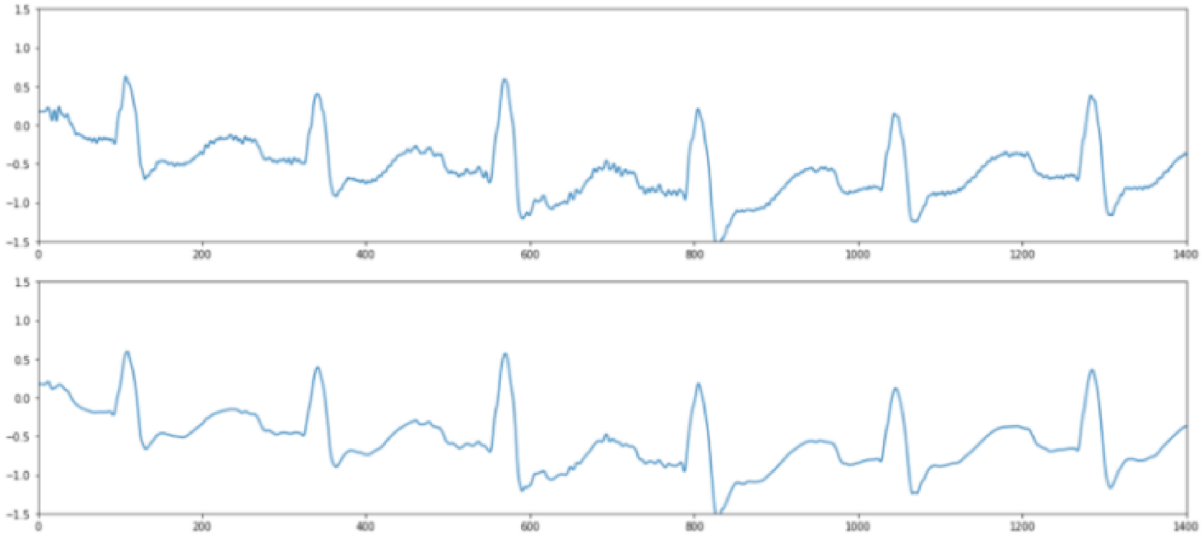


Figure 6. ECG signal (a) before and (b) after filtering and de-noising

3.2. Train the CNN model and test the accuracy of the model

Fig.7 shows the accuracy of the training model in the ideal state versus the accuracy of the training model for the actual project and Fig. 8 shows the loss of the training model in the ideal state versus the loss of the training model for the actual project.

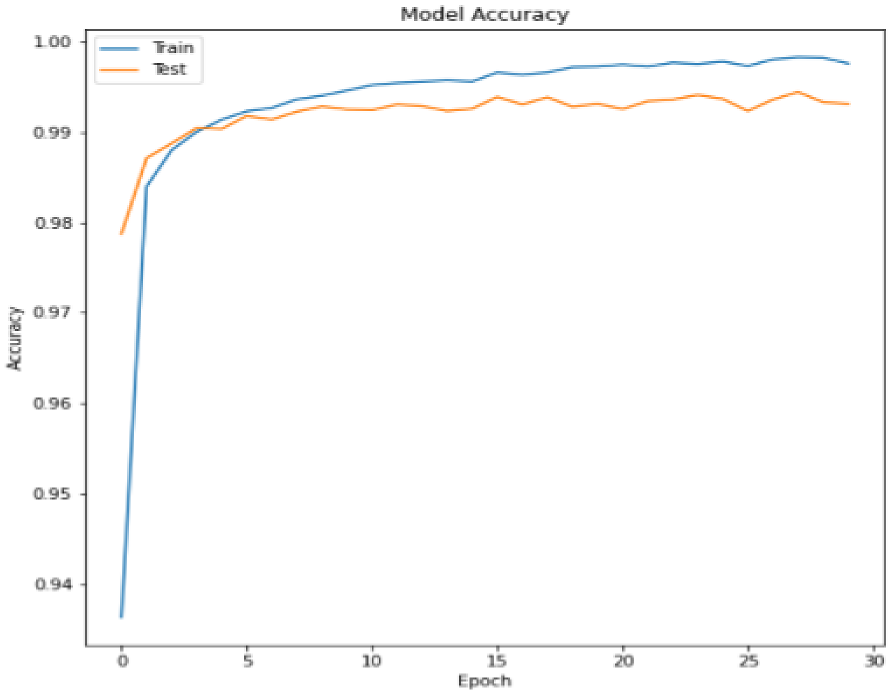


Figure 7. The accuracy of the training model in the ideal state versus the accuracy of the training model for the actual project

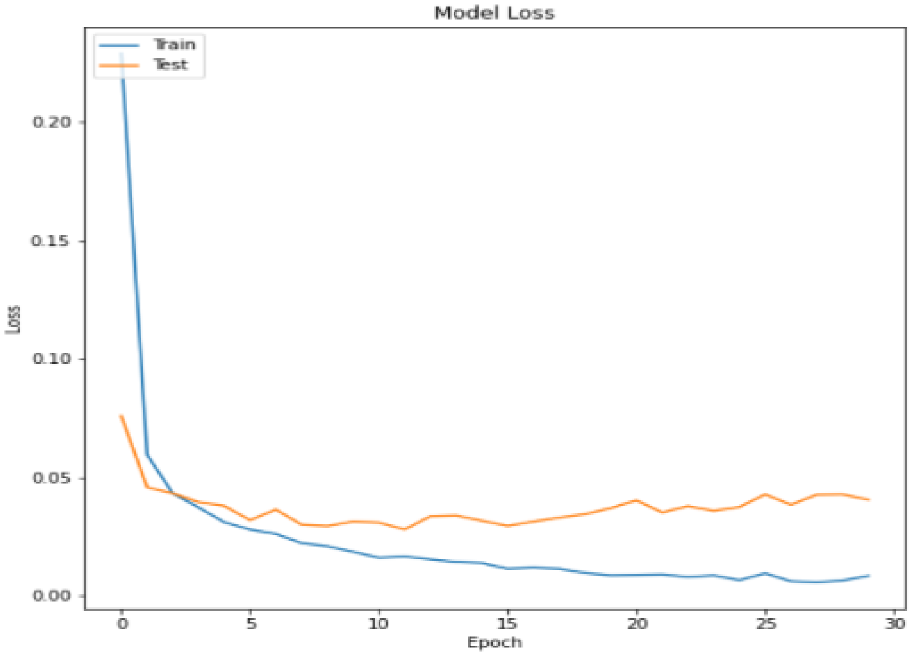
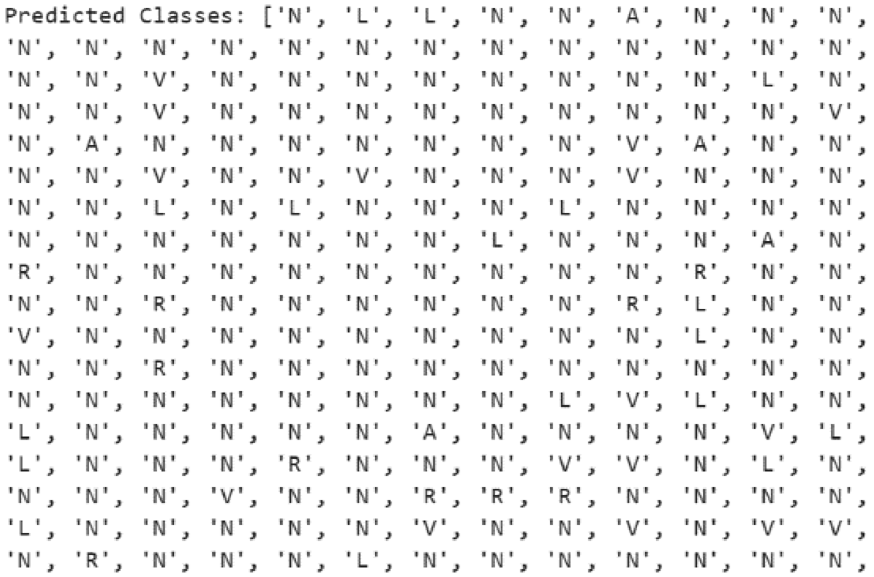


Figure 8. The loss of the training model in the ideal state versus the loss of the training model for the actual project

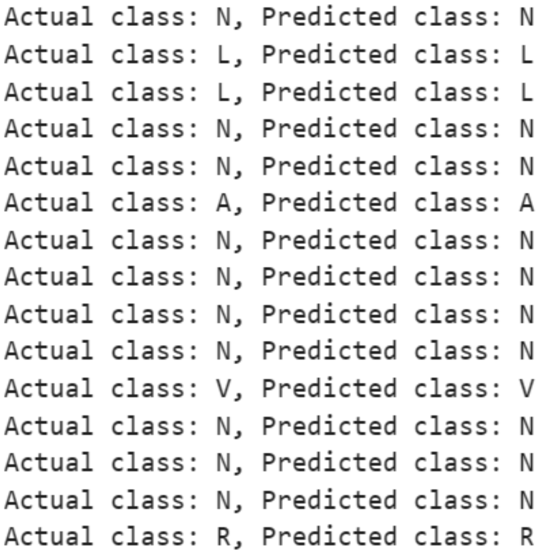
It can be seen that the training model of the convolutional neural network has been highly accurate and has been able to use this convolutional neural network training model to judge the categories of the original ECG signals.

Fig.9 shows the types of ECG signals predicted by the training model. Fig.10 shows the comparison of the types of ECG signals predicted by the training model with the actual types of ECG signals.



```
Predicted Classes: ['N', 'L', 'L', 'N', 'N', 'A', 'N', 'N', 'N',
'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N',
'N', 'N', 'V', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'L', 'N',
'N', 'N', 'V', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'V',
'N', 'A', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'V', 'A', 'N', 'N',
'N', 'N', 'V', 'N', 'N', 'V', 'N', 'N', 'N', 'V', 'N', 'N', 'N',
'N', 'N', 'L', 'N', 'L', 'N', 'N', 'N', 'L', 'N', 'N', 'N', 'N',
'N', 'N', 'N', 'N', 'N', 'N', 'N', 'L', 'N', 'N', 'N', 'A', 'N',
'R', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'R', 'N', 'N',
'N', 'N', 'R', 'N', 'N', 'N', 'N', 'N', 'N', 'R', 'L', 'N', 'N',
'V', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'L', 'N', 'N',
'N', 'N', 'R', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N',
'N', 'N', 'N', 'N', 'N', 'N', 'N', 'N', 'L', 'V', 'L', 'N', 'N',
'L', 'N', 'N', 'N', 'N', 'N', 'A', 'N', 'N', 'N', 'N', 'V', 'L',
'L', 'N', 'N', 'N', 'R', 'N', 'N', 'N', 'V', 'V', 'N', 'L', 'N',
'N', 'N', 'N', 'V', 'N', 'N', 'R', 'R', 'R', 'N', 'N', 'N', 'N',
'L', 'N', 'N', 'N', 'N', 'N', 'V', 'N', 'N', 'V', 'N', 'V', 'V',
'N', 'R', 'N', 'N', 'N', 'L', 'N', 'N', 'N', 'N', 'N', 'N', 'N',
```

Figure 9. Outputs of the types of signals predicted by the training model



```
Actual class: N, Predicted class: N
Actual class: L, Predicted class: L
Actual class: L, Predicted class: L
Actual class: N, Predicted class: N
Actual class: N, Predicted class: N
Actual class: A, Predicted class: A
Actual class: N, Predicted class: N
Actual class: N, Predicted class: N
Actual class: N, Predicted class: N
Actual class: N, Predicted class: N
Actual class: V, Predicted class: V
Actual class: N, Predicted class: N
Actual class: N, Predicted class: N
Actual class: N, Predicted class: N
Actual class: R, Predicted class: R
```

Figure 10. Comparison of the outputs of the types of ECG signals predicted by the training model with the actual types of ECG signals

Finally, put in the original ECG signal, determine the type of signal and, depending on the type, analyse whether the ECG signal is normal or not, and analyse it to determine the cause of the disease. Fig.11 shows that the categories predicted accurately by the model are the majority of the true categories. In the confusion matrix, when ' 0 ' is used to represent a specific type of ECG signal, the high frequency of ' 0 ' in the predicted and actual categories indicates that the model 's prediction of this type of signal is very consistent with the real classification. This consistency indicates that the model is very accurate in identifying such ECG signals.

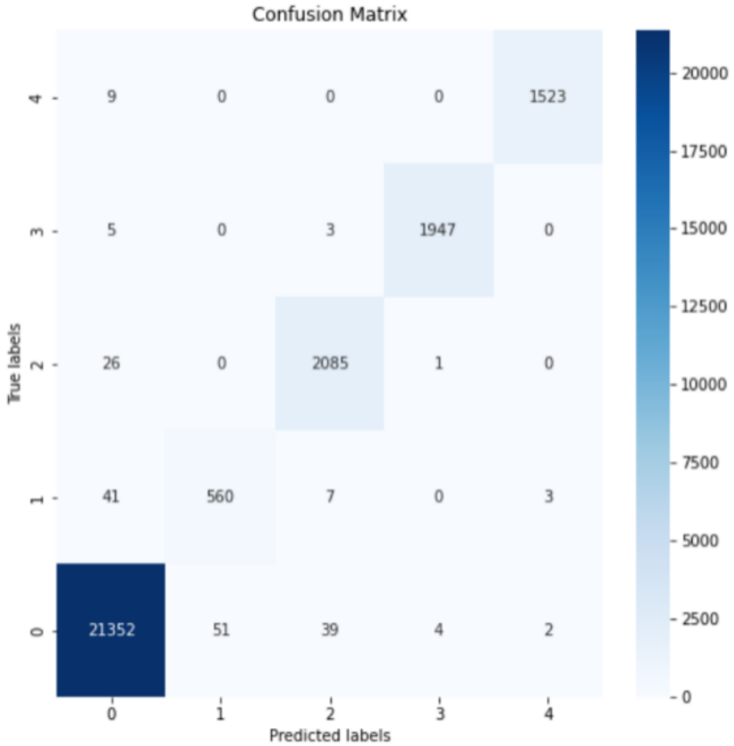


Figure 11. Confusion matrix of the results of the training model

4. Literature References

In the field of wearable healthcare devices, signal processing is a critical component for accurate health monitoring. Lee and Yang (2023) refined heartbeat detection using Doppler radar signal preprocessing to enhance signal quality amidst noise [1]. Complementing this, Yang et al. (2018) proposed an adaptive noise cancellation technique, showcasing the efficacy of adaptive filters in wearable devices [2]. Nosrati and Tavassolian (2018) contributed to the accuracy of heartbeat detection by considering chest-wall acceleration in Doppler radar systems, a crucial factor for wearables during user movement [3]. Zhao et al. (2020) took advantage of CNNs to efficiently recognize bowel sounds in wearables, balancing computational complexity and performance [4]. Lastly, Zhang et al. (2021) advanced heartbeat classification with a hybrid time-frequency analysis using transfer learning, demonstrating the potential of deep learning in processing complex signal patterns for health monitoring [5]. In addition to these studies, several other notable advancements have been made. For instance, Thilagavathy R et al. developed a novel algorithm for real-time ECG feature extraction and classification using a combination of time-domain and frequency-domain features, which improved the detection of cardiac arrhythmias. Furthermore, Badawi A A et al introduced a machine learning-based approach for activity recognition and health monitoring using data from multiple wearable sensors, highlighting the potential of multi-sensor fusion for comprehensive health assessments. More recently, research has focused on the development of lightweight and energy-efficient algorithms specifically designed for wearable devices. For example, Kristiani E et al proposed a deep learning model optimized for edge computing in wearable devices, which allows for on-device processing and reduces the need for continuous cloud communication, thereby saving power and enhancing user privacy. These studies showcase the progression towards more precise and non-intrusive health monitoring through wearable devices.

The literature review underscores the evolving role of signal processing and machine learning in enhancing the accuracy and efficiency of wearable healthcare devices for health monitoring. It highlights the integration of various techniques, such as adaptive noise cancellation and deep learning algorithms, to improve the detection and classification of health-related signals.

Transitioning from these advancements, our approach introduces an innovative method that synergizes wavelet transform and convolutional neural networks (CNNs) to address the challenge of noise in ECG signals and to facilitate precise, real-time heartbeat classification for wearable devices.

5. Summary

With the rapid development of signal processing technology and medical technology, this technology can be applied to wearable monitoring equipment to help people understand the type of detected ECG signals anytime, anywhere and in time, and facilitate people 's lives. In this paper, a wavelet transform is proposed to filter and denoise the initial ECG signal, and the ECG signal in the MIT data set is successfully filtered, and a smoother curve is obtained. Then, an ECG signal recognition and classification model based on convolutional neural network (CNN) is constructed. The convolutional neural network model of the project was successfully trained, and the accuracy of signal type reached 99 %. Finally, the ECG signal images are classified. In addition, the technology is expected to be integrated with the health management platform, allowing users to access and analyze their health data in a timely manner, not only heart rate, but also daily steps, body temperature and other parameters. Allow personalized and accurate health data identification and management.

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