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Classification of heart diseases using time-frequency representations of electrocardiogram signals by transfer learning networks

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Abstract:

It is crucial to monitor and diagnose cardiac function early to prevent the development of future, more severe issues. This study categorized 193 male and female subjects into three groups based on their ECG signals obtained during an exercise test: healthy, myocardial infarction, and left bundle branch block. The data were then processed and converted into images representing three time-frequency representations: a spectrogram, a scalogram, and a spectrum. These images were used as input for two pre-trained networks through transfer learning. The ResNet-18 and GoogLeNet networks were utilized in this study. The ResNet-18 network achieved an accuracy of 88.64% for the spectrogram, 98.41% for the scalogram, and 83.33% of the spectrum. The results for the GoogLeNet network were as follows: 77.27% for the spectrogram, 97.62% for the scalogram, and 78.57% of the spectrum.

Keywords: Heart abnormality; ECG; Transfer learning; Spectrogram; Scalogram; Pspectrum

1. Introduction

Heart complications are the most common type of disease spread around the world that many people deal with. Also, deaths caused by heart disease are in first place according to the statistics of the World Health Organization and every year it kills about 18 million people around the world. Given the importance of this issue, the need for timely and correct diagnosis of a person's heart complications before the disease reaches higher stages is clear to all. Nowadays, there are different methods like nuclear imaging, ultrasound imaging, etc. For checking cardiac function. But one of the least expensive, most accessible, and most reliable types to check the heart's health is using an electrocardiogram device, which displays the waveform from the beginning to the end of a cardiac cycle by recording the electrical potential of the heart muscle. An electrocardiogram is one of the most common ways of observing how the heart works. The use of electrocardiograms helps to understand all types of heart arrhythmias. By connecting multi-channel leads to the patient's body, this device monitors all stages of heart muscle activity, and the doctor can diagnose the origin and type of the disease based on the abnormal changes in the formed waveform, compared to the condition of a normal person. In light of the heightened sensitivity of diagnosis and prediction in medicine, it is imperative to enhance the precision of previous studies. The reliable substitution of neural networks for humans necessitates extensive data training and precise parameter tuning to achieve enhanced accuracy. The objective of this study is to improve the accuracy of an artificial neural network for the diagnosis of cardiovascular disease. The selected pre-trained networks yielded superior results compared to those observed in previous studies. Transfer learning using pre-trained networks provided acceptable results in other applications. It also requires less time to set parameters and network design. In numerous previous studies, the ECG signal was employed directly for

training and classification, in CNN networks. Given that the heart signal is a time series signal, LSTM networks may be employed directly for this purpose. The utilization of convolutional networks is contingent upon the data being presented to the network in the form of images, as this is expected to result in enhanced accuracy. While convolutional networks are employed in this work, it is preferable to transform the signals into images in the frequency domain. This resulted in an improved level of classification accuracy. Furthermore, the examination and comparison of three distinct representations of a signal in the frequency domain are of considerable significance. This will facilitate the identification of the representation that is most effective in diagnosing individuals with cardiac conditions. In this work, we examined two common conditions, myocardial infarction and the Left Bundle Branch Block (LBBB). The test subjects are of different age ranges and both sexes, after recording data from them and performing the required pre-processing on the recorded signals such as removing noise, we converted them into time-frequency images. We converted the signals of every person into a scalogram, spectrogram, and pspectrum as input of deep convolutional neural networks [1]. In recent years, much research has been conducted into deep networks and their use as a relatively suitable surrogate for humans in decision-making and diagnosis [2]. The development of deep networks has helped resolve classification issues, especially in the medical area for diagnosis and treatment. Moreover, most researchers favor the use of pre-trained networks because of their high efficiency. Powerful pre-trained networks such as ResNet-18 [3] and GoogLeNet [4] are used in this work, and by fine-tuning them, the weights and parameters can be changed according to the desired goal. A lot of important research has been done on this. Diker et al. Used the PTB database, which included ECGs of 148 patients and 80 normal subjects, which were converted to spectrogram images as inputs to 3 pre-trained networks. They used networks such as AlexNet, VGGnet, and ResNet-18. The precision achieved for each network was 83%, 76%, and 82% respectively. Of course, it is worth mentioning that the specific nature of this task for each network is 62%, 50%, and 54% respectively [5]. In a similar work, Singh et al. Used 70 ECG samples of their class 3 OSA problem. They divided training and testing data equally, meaning that 35 samples were considered for network formation and 35 samples for network testing. The network they used was AlexNet, whose input was fed with spectrogram images of the data used. They formed the desired network up to 2 epochs and achieved 86% accuracy [6]. Yaldirim et al. published their research to classify 2 classes of normal people and diabetes mellitus patients from 15 1-hour ECG data of healthy people and also 15 ECG data of diabetes mellitus patients. They also used only spectrogram images of signals for the input of deep networks. The difference in their work compared to the previous two studies is that in addition to the 1D signal, they used a spectrogram for 2D CNN networks to train Alexnet, VGG, ResNet-18, and Dense net. The accuracy of this work was 95%, 96%, 95%, and 97% respectively [7]. Huang et al. Used the MIT-BIH arrhythmia database. In this work, they examined 5 types of heartbeats, which are: normal beat (NOR), left bundle branch block beat (LBB), right bundle branch block beat (RBB), premature ventricular contraction beat (PVC), and atrial premature. Contraction beat (APC). First, they performed 2D spectrogram images from ECG signals using a short-time Fourier transform to train convolutional networks. A learning rate of 0.001 and a batch size of 2500 were used for this network, which was designed with an unbalanced data count and reached a remarkable accuracy of 99%. They also compared their network with the 1D network, and finally, the resulting accuracy of the 1D network was 90.93% [8]. The next work that Salem et al. Has done is to use a pre-trained network called DenseNet. After converting the ECG signals of four different datasets into spectrogram images, they gave it to the input of the network, but after extracting the features by the middle layers of the convolutional network, from an external classifier which was SVM with -10 folds to classify the data. They finally got 97.30% accuracy [9]. Alqudah et al., in their research, used both types of Spectrogram displays and types of deep convolutional networks for classification. In this work, they solved the problem more comprehensively. The data set used was the standard MIT-BIH six-class arrhythmia. The different spectrogram displays used in this work were: Log-scale and Mel-Scale in addition to Bi-Spectrum and the third-order cumulant. Also, 4 different network architectures named AOCT-NET, Mobile-Net, Squeeze-Net, and Shuffle-Net have been classified in this research. The highest accuracy obtained among the tested networks overall was for Mobile net architecture with 93.8%. Also, the highest accuracy rate among different Spectrogram displays belongs to the bispectrum with 93.7% accuracy [10].
Additionally, other research has been conducted to examine the various classifications of heart disease. Acharya et al. Attempted to develop an automated system for the detection and localization of myocardial infarction using electrocardiograms. A data set comprising 52 healthy subjects and 148 subjects with MI was employed. The sole cardiac condition under investigation was MI. However, the researchers proposed an automated detection of 10 types of MI and their locations. A total of 12 features was manually extracted from the ECG signal to detect MI, resulting in an accuracy rate of 98.8% [11]. Additionally, Li and Zhou employed a classification approach utilizing wavelet packet entropy and random forests for ECG data. The MIT–BIH Arrhythmia Database was employed, and the entropy of each terminal node in the wavelet packet tree was calculated as a feature. The algorithm, which integrated wavelet packet entropy and the time between the R peaks of two heartbeats, achieved an accuracy of 94.61% when evaluated using random forests [12]. In another study, Diker et al. Investigated the application of artificial neural networks (ANN), support vector machines (SVM), and k-nearest neighbor (k-NN) machine learning methods for the classification of electrocardiogram (ECG) signals as normal or abnormal. The highest performance was achieved by SVM, at 85.1%. The open-source PTBDB database was used in this study [13]. The last one is Josaga's work, where he investigated Atrial Fibrillation by utilizing three distinct 2D representations of ECG sig-

nals. In his research, Josaga applied CNNs to compare the effectiveness of three different visualization techniques: scalogram, spectrogram, and attractor reconstruction. Using the MIT-BIH Atrial Fibrillation (AFIB) database, his approach yielded classification accuracies of 94% for both the spectrogram and scalogram representations, and 89% for the attractor reconstruction [14].

2. Material and method

2.1 Dataset

The methodology of this study is illustrated in the block diagram provided in figure 1. The dataset was acquired from a clinical environment, comprising participants from four distinct cardiovascular categories: normal, myocardial infarction, left bundle branch block (LBBB), and ischemia. However, ischemia data were subsequently excluded from the analysis due to inconsistencies that rendered it unsuitable for the intended scope of this study. The final dataset used in this investigation consisted of 193 normal records, 78 records from individuals diagnosed with myocardial infarction, and 88 records from individuals with LBBB. The participants, spanning both genders, were aged between 50 and 70 years, ensuring a relevant demographic for the study of age-related cardiac conditions. Participants were admitted to the clinic in the morning hours and were administered a radiopharmaceutical agent before any testing. This radiopharmaceutical was used to enhance gamma imaging, a nuclear medicine technique employed to visualize functional processes in the body. Following gamma imaging, participants underwent a graded exercise test, which lasted between 5 and 15 minutes based on individual fitness levels and clinical indications. The exercise test, an essential component of this study, aimed to induce cardiac stress, under which latent cardiovascular abnormalities might manifest, thus providing more comprehensive diagnostic insights. All electrocardiography data were recorded using a 12-lead ECG treadmill system developed by Avecina. This system was chosen for its robust performance in clinical stress-testing environments. Exercise ECGs are particularly informative for identifying ischemic changes or arrhythmias that may not be evident during resting ECG. The use of a treadmill allowed for standardized stress induced, while continuous ECG monitoring provided real-time assessment of cardiac electrical activity. To minimize external influences and ensure high-quality signal acquisition, the signal recording environment was meticulously controlled. The recording room was electromagnetically shielded to prevent interference from ambient electronic devices, human activity, and environmental noise. Moreover, no strong magnetic or electrical fields were present in the vicinity of the record-

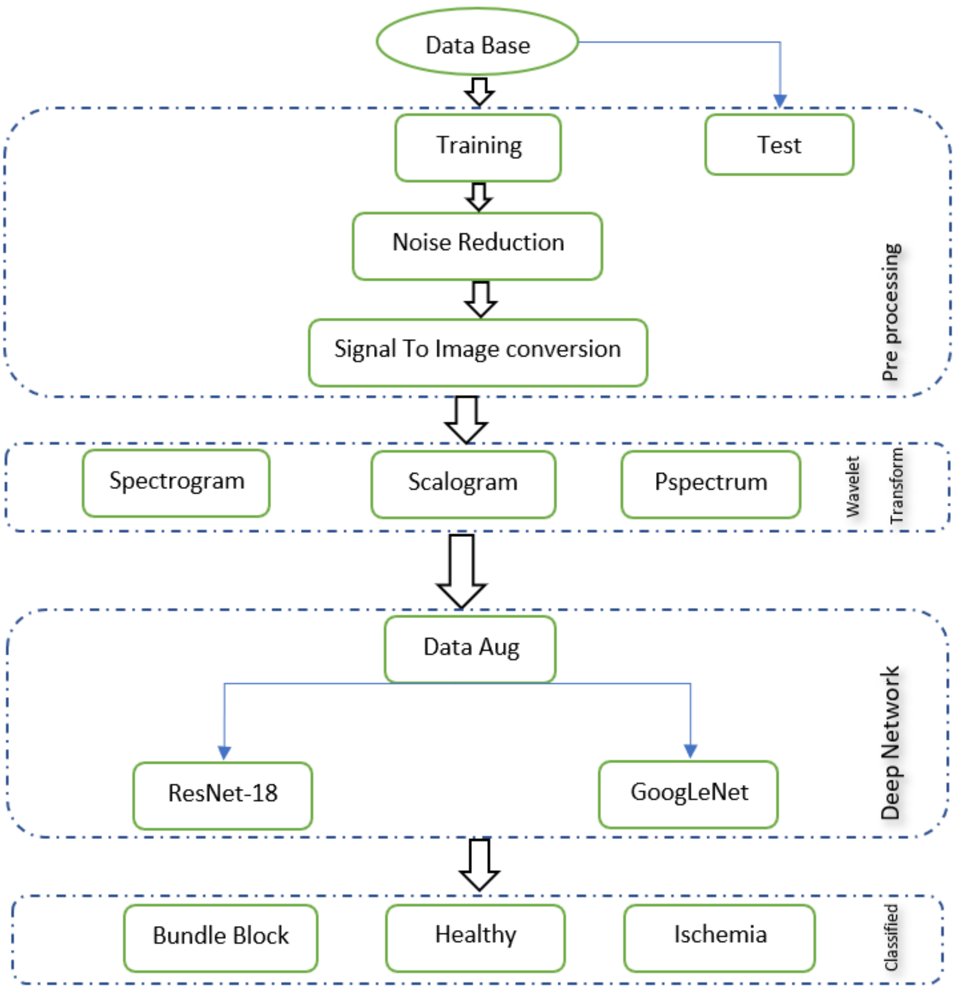

Figure 1. The block diagram of the method.

ing area, ensuring a clean, undistorted ECG signal. These precautions were critical in preventing artifacts that could compromise the integrity of the recorded data. The ECG signals were continuously recorded from the second lead of the 12-lead system, commonly regarded as a reliable lead for monitoring and detecting arrhythmic events or ischemic changes. A sampling rate of 256 Hz was employed, ensuring that the temporal resolution was sufficient to capture all relevant cardiac events, including rapid changes in heart rate and rhythm during exercise. The signals were digitized at a 12-bit resolution, providing a high degree of precision in the recorded data, with each sample capable of distinguishing 4,096 discrete levels of voltage. Data collection was conducted at the Parto Nuclear Medicine Center, a specialized facility located in Khorram Abad, Iran. This center was selected for its expertise in both nuclear medicine and cardiovascular diagnostics, ensuring the availability of the necessary equipment and clinical expertise for this study. Importantly, all participants provided informed consent before enrolling in the study, following ethical guidelines and ensuring their voluntary participation. Informed consent protocols were strictly adhered to, ensuring that participants were fully aware of the nature, purpose, and potential risks of the study. To ensure the reliability and accuracy of the dataset, all data labeling was rigorously validated by a panel of medical experts. The classification of participants into the categories of normal, myocardial infarction, and LBBB was verified by two senior clinicians. Dr. Sharifi, a seasoned cardiologist, and Dr. Jafarian, a nuclear medicine specialist, reviewed the ECG records and clinical data to confirm the accuracy of the diagnoses. Their involvement in the verification process added a layer of credibility to the dataset, ensuring that it was appropriately categorized for subsequent analysis. The precision of data labeling was critical to the downstream analyses, particularly in the context of machine learning applications, where mislabeled data could lead to erroneous conclusions. By involving domain experts in the verification process, the study ensured that the dataset would be a reliable foundation for further computational modeling and statistical evaluation. In summary, the data collection process for this study was conducted under highly controlled conditions, with stringent protocols in place to ensure the accuracy and reliability of the ECG recordings. The comprehensive verification of data labels by experienced clinicians further enhanced the quality of the dataset, making it suitable for detailed analysis in the context of myocardial infarction and LBBB diagnosis.

2.2 Preprocessing

Despite data recording under optimum conditions, the presence of noise and signal disturbance is undeniable [15]. Initially, we used the wavelet transform to reduce the noise of the recorded signals. We obtained Wavelet coefficients using Symlet 10 in MATLAB software [16]. After this stage, we will proceed to the normalization of the amount of data. In this section, due to the amount of data of 3 classes is unbalanced. For improved training and to avoid biasing the network towards one of the classes, all data for the three classes are randomly divided into as few classes as possible. We've narrowed the data in each class down to 78. Furthermore, in many earlier works, they avoid this practice and solve this problem by using committee machines and applying data with different weights to the network. In this work, after reducing the data of the classes, we have done Data augmentation images. Since the accuracy of the results of deep networks increases with the increase in the amount of data with independent features, we have also increased data for a reliable result.

2.3 Time-Frequency representation

2.3.1 Scalogram

A type of time-frequency representation is obtained from the continuous wavelet transform. It converts the ECG signal, which is a continuous-time signal, into a time-frequency space with a function and a mother wavelet. The mathematical equation for transformation to continuous wavelets is shown in (Eq. 1):

$$X_{\omega}(a,b) = \frac{1}{|a|^{\frac{1}{2}}} \int_{-\infty}^{\infty} x(t)\psi(\frac{t-b}{a})dt \tag{1}$$

where ψ is a continuous function in time-frequency, known as Kernel wavelet or mother wavelet function. Also, Ω are the wavelet coefficients. The input signal will be x, and a and b are the comparison and positional parameters, respectively [17]. We prepared these images using the CWT command in MATLAB software and also considered the Morse wavelet as the default wavelet, then used them as inputs of pre-trained deep networks.

2.3.2 Spectrogram

Another type is the time-frequency representation of the signal, which is the result of the output of the short-time Fourier transform of the signal. The signal will be split into smaller time slices, and a Fourier transform will be applied to each of them [18]. After doing this, each of the intervals will be converted into a frequency spectrum, and by assigning a color code according to the value of the coefficients, we'll have a color map for the main signal. By using MATLAB software, we converted the ECG signals in the database to color images which can be used for deep neural networks using the spectrogram (X) command [19].

2.3.3 Pspectrum

Whenever we need to display the signal strength spectrum, we use a pspectrum command in MATLAB software [20]. The difference between this display and the spectrogram in plain language is that the spectrogram plots the spectrum of the short-time Fourier transform of the input signal, while the pspectrum displays the power spectrum which is used to analyze the signals in the domain Frequency and time frequency are used [21].

2.4 Pre-trained convolutional neural networks

These days, because of the proper efficacy of artificial neural networks, this powerful algorithm is widely used for machine learning. Neural networks have proven to be effective in solving problems such as classification and regression in different areas. Artificial neural network, which is a subset of artificial intelligence and machine learning, was first

introduced by McCulloch and Pitts in 1943 by modeling the structure of neural message transmission in the human brain [22]. They first introduced a single-neuron perceptron network. As can be seen in (Fig. 2), two inputs for this neuron, which are sample features, are entered into the network. After multiplying with the weights on the branches of the neuron, the obtained value moves towards the activation function, which in this figure is a linear function, and if the threshold limit of this function is reached, the neuron is activated, otherwise, the output is zero. This is a very simple example of a primitive network of single-neural perceptrons. With the passage of time and the increase in the speed of calculations and of course the progress and development of neural networks, as well as the emergence of cases such as error backpropagation to solve problems that have nonlinear separability, deep networks were designed. As a result of deep networks, the use of this algorithm has become more popular. Introduce things like the establishment of hyperparameters, the application of various optimization methods, and the definition of new activation functions added to the appeal and efficiency of artificial networks.
This has led the developers of deep neural networks to develop new network architectures every year and introduce powerful trained networks. ResNet-18 is one of the most powerful and widely used networks when it comes to classification issues. This network was introduced by Kaiming He et al. (2015). This network aims to rewrite the network formula and reduce the complexity of deep networks using the same parameters. The proposed network has shown that it is easier to optimize than normal networks, and it is also more successful in increasing the accuracy of the network in classification compared to normal networks in higher depths. Another network introduced by Christian Szegedy was named Google Net in 2014. They proposed a 22-layer network in the ILSVRC14 challenge. The advantage of this network is stated in the improvement of internal computing resources, which simultaneously increases the depth and width of the network, and still provides users with the quality of results while keeping the cost of computing constant. This network has won the first rank in the ILSVRC14 challenge. Once the data had been converted to spectral images, we resized it to the size of the network inputs. In our work, we used both ResNet-18 and GoogLeNet networks and changed all 3 groups of images to 224*224*3 dimensions to fit them as input of these networks.

2.5 Performance evaluation

To validate this work's accuracy which you can see in (Eq. 2), used.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

To validate this work's accuracy which you can see in (Eq. 2), has been used. TP (True Positive) means the model correctly predicts the positive class, TN (True Negative) means the model correctly predicts the negative class, FP (False Positive) means the model incorrectly predicts the positive class when it is negative and FN (False Negative) means the model incorrectly predicts the negative class when it is positive.

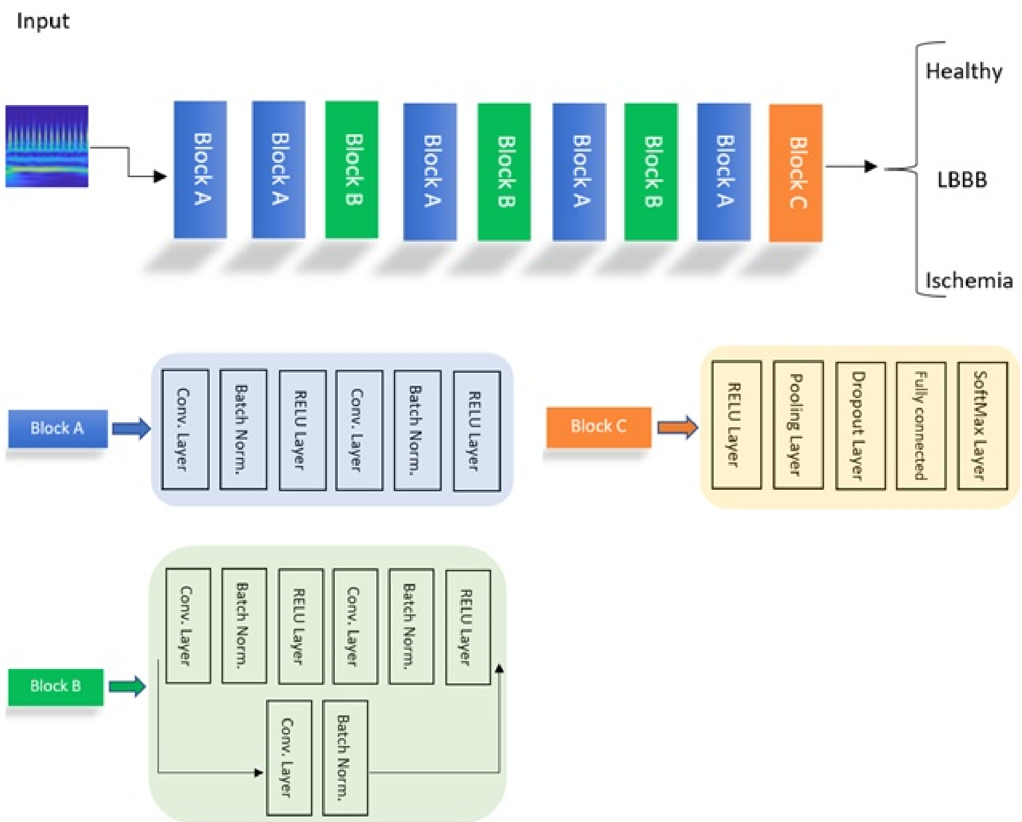

Figure 2. The structure of pre-trained ResNet18 used in this research.

3. Results

The experiments for the analysis were carried out on a computer with an Intel(R) Core i7 CPU and 8 GB of memory, using MATLAB 2021b. In the first result of our work, we removed the noise of the ECG signal. A sample of the signal before removing the noise and also after applying the transform to wavelets to reduce the noise.
After noise removal, we transform the signal into three classes of time-frequency representation and prepare them for the next stage we should use them as input for transfer learning networks. An example of time-frequency image output can be seen in (Fig. 3).
After obtaining time-frequency images from healthy and diseased ECG signals, we fed them to deep-learning networks for feature extraction and classification. We utilized 78 samples for network training and 20% for network validation during training. Also, we use data augmentation like rotation, rescaling, etc. To increase the size of the dataset to decrease the possibility of overfitting. Table 1 shows two different networks with different hyperparameter settings are used for this task. To achieve the highest accuracy, different batches and different optimization functions were used. Also, considering the early stopping point during network training, different learning rates were also used, and the final results were summarized in the following table, showing some of them. This work used a variety of trials and errors to define hyperparameters. For example, batches 15 and 10 were also used. It is important to choose the number of data to be trained in each iteration because choosing a very high value is associated with the possibility of reducing the accuracy, and also choosing a very low value, in addition to increasing the time and volume of calculations, causes the updating of the weights to be prolonged, and the tolerance Changes in weights will be drastic. Finally, optimally, we obtained the highest accuracy value using batch 10. Since choosing a fixed learning rate in network training faces problems such as increasing computation time or network divergence, in this work, a time-varying learning rate is used at the beginning of the network training process, when the error rate is high, from the steps use large to reach the minimum point and after some time and check the small changes of the error, take advantage of small steps so that he does not lose the optimal place and does not cross it. The initial set rate was 0.0001. Also, we discussed various optimization methods such as SGDM, ADAM, and RMSPROP to test and check the accuracy of the network by using different optimization algorithms. Ultimately, we put

Table 1. Summary of different parameters.

Approach	Network	Batch	Accuracy (%)
Scalogram	ResNet-18	10	**98.41**
	GoogleNet	15	97.62
Spectrogram	ResNet-18	10	**88.64**
	GoogleNet	15	77.27
Pspctrum	ResNet-18	10	**88.10**
	GoogleNet	15	78.57

the most appropriate optimization algorithm in this work, SGDM. It should be noted that to prevent the network from diverging in reaching the optimal weights, we defined a stop criterion for the network, which, if the downward trend of the validation number is observed for 5 consecutive epochs, the training of the network is stopped and the last previous value of the obtained accuracy is Decreasing the validation number to declare as the final accuracy of the network.
In (Fig. 4) The images are associated with the test data of the trained networks. The first row represents a sample of spectrogram images, the middle row of scalogram images, and the lower row of spectrum images. The numbers inserted at the top of each of the images signify the accuracy of the detection of the desired network in the correct determination of the corresponding class.

4. Discussion

Heart diseases remain one of the leading causes of mortality worldwide, with early detection, playing a crucial role in preventing many of these fatalities. Timely and accurate diagnosis of heart failure and other cardiac conditions can significantly reduce the associated morbidity and mortality rates. In this study, we explore the potential of artificial intelligence, specifically deep learning, to diagnose various cardiac diseases through the analysis of electrocardiogram (ECG) signals. The research focuses on classifying individuals into three categories: healthy subjects, those who have experienced a myocardial infarction, and those with left bundle branch block (LBBB), based on cardiac signals recorded during exercise stress tests. To enhance the accuracy of the classification, the raw ECG data is preprocessed and transformed into time-frequency representations. In particular, the spectrogram, scalogram, and pspectrum are employed as key visualizations of the signal, serving as input to two pre-trained deep convolutional neural networks—ResNet-18 and GoogLeNet. This approach demonstrates the efficacy of using deep learning techniques in the automated classification of cardiac condi-

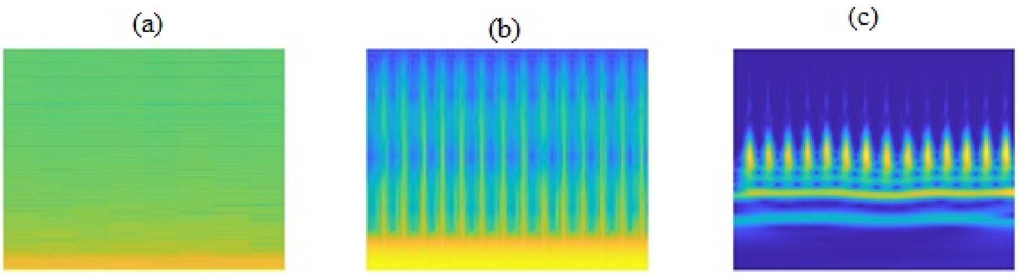

Figure 3. (a) Spectrogram, (b) Pspectrum, and (c) Scalogram.

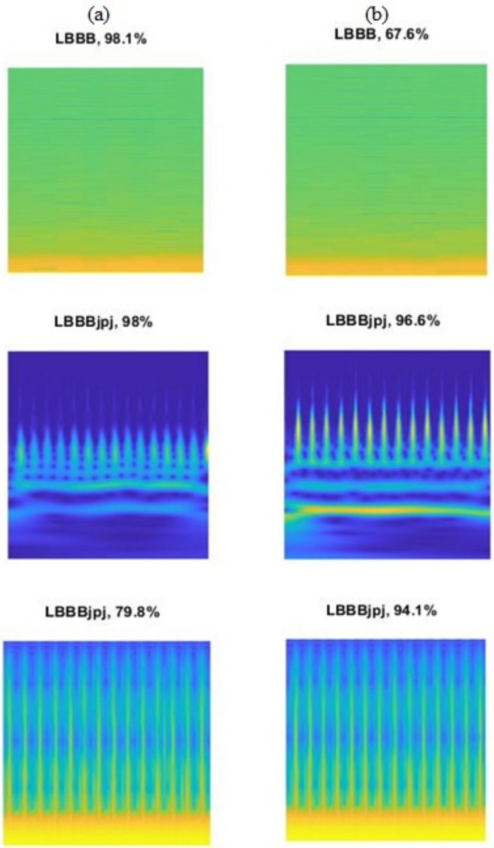

Figure 4. The accuracy achieved in this study by utilizing the networks was determined by separating three different frequency domain representations of the LBBB sample. (a) The results obtained by the ResNet network (b) The results obtained by the GoogleNet network.

tions. Both ResNet-18 and GoogLeNet have shown strong potential in accurately distinguishing between the different categories of heart disease. By leveraging these advanced architectures, the study achieves robust performance in the detection of cardiac arrhythmias, demonstrating the effectiveness of time-frequency imaging in enhancing diagnostic accuracy. While previous research has yielded encouraging results in the early detection of arrhythmias, this study introduces the novel application of time-frequency images to improve classification outcomes. Furthermore, this work offers a comparative analysis of the results with those of earlier studies, underscoring advancements in the use of convolutional neural networks (CNNs) for heart disease diagnosis. The findings highlight the potential of integrating AI and deep learning models into clinical practice for early detection and diagnosis, contributing to more efficient and timely interventions for heart disease patients. The table below presents a detailed comparison of the current study's results with previous research, emphasizing improvements in diagnostic accuracy through innovative methodologies.

5. Conclusions

The detection and classification of cardiac arrhythmias is a critical challenge in modern medicine, demanding robust automated solutions. This study leverages ECG data from 193 individuals, classified into healthy, myocardial infarction, and Left Bundle Branch Block (LBBB) groups, to explore AI-driven diagnostics. Pre-trained neural networks ResNet-18 and GoogLeNet were fine-tuned using three time-frequency ECG representations: spectrogram, scalogram, and pspectrum. Scalogram with ResNet-18 achieved the highest accuracy (98.41%). The results

Table 2. Comparison with other works.

Articles	Dataset	Input	Network architecture	Accuracy
Diker et al [5]	PTB	Spectrogram	Alexnet	83%
			VGGnet	76%
			Resnet18	82%
Singh et al [6]	OSA	Spectrogram	Alexnet	86%
Yaldirim et al [7]	-	Spectrogram	Alexnet	95%
			VGGnet	96%
			Resnet18	95%
Huang et al [8]	MIT-BIH arrhythmia	Spectrogram	CNN	90.93%
Salem et al [9]	Four different databases	Spectrogram	Densnet	97.3%
Alqudah et al [10]	Standard MIT-BIH six-class arrhythmia	Spectrogram	Mobilenet	93.8%
Acharya et al [11]	PTB	1-D ECG signal	KNN	98.8%
Li and Zhou [12]	MIT-BIH arrhythmia	1-D ECG signal	Random Forest	94.61%
Diker et al [13]	PTBDB	1-D ECG signal	SVM	85.1%
Josaga [14]	MIT-BIH AFIB	Scalogram, Spectrogram Attractor	CNN	94% 94% 89%
OURS		Spectrogram	Resnet18	88.64%
			GoogLenet	77.27%
OURS		Scalogram	Resnet18	98.41%
			GoogLenet	97.62%
OURS		Pspectrum	Resnet18	83.33%
			GoogLenet	78.57%

highlight the potential of AI for arrhythmia detection, suggesting ensemble techniques and combined transforms for improved diagnostic performance and personalized care.

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Authors contributions
Authors have contributed equally in preparing and writing the manuscript.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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