Enhanced Arrhythmia Detection Through Wavelet Scattering and Deep Learning Techniques

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ABSTRACT: *Arrhythmia is a condition where the heart beats irregularly, too fast, or too slow. It can be caused by various factors such as heart disease, high blood pressure, or electrolyte imbalances. Arrhythmia is defined as an irregularity in the heartbeat rhythm. Recently, many people were affected by cardiac diseases, due to covid19 [1]. So, we proposed the deep learning model to automate the detection and classification process to help the doctors for quick results. We use ECG signals that were downloaded from the Physio-Net database as our input. The Dataset undergoes a process to change the signal into a space with many dimensions using some basic functions. Using wavelet scattering, we extract the characteristics. Wavelet scattering is a signal processing technique that decomposes a signal into its constituent waveforms, allowing for the identification of patterns that may indicate arrhythmias. Then converting 1D ECG Signal to 2D scalogram images by using Continuous Wavelet Transform (CWT). Arrhythmia detection is done by using deep learning (Efficientnet-B0) model and compared it with other models such as Efficientnet-B0 with 97.9%, Alexnet model gives 86.67%, Resnet50 by 97.78%, and Densenet with 89.26% accuracy.*

Keywords*:* Arrhythmia, Wavelet Scattering, Deep Learning, Continuous wavelet Transform, Efficientnet-B0, Scalogram.

1. INTRODUCTION

Arrhythmias are irregular heartbeats that can result in major medical issues such as cardiovascular disease [2], stroke, and a sudden cardiac arrest. Early detection and diagnosis of arrhythmia [3,4] can be crucial in preventing these complications. One approach to detecting arrhythmia is using a combination of wavelet scattering and efficient netb0. Wavelet scattering is a feature extraction method that decomposes a signal into its constituent parts, allowing for more precise analysis. It has three layers namely, convolution, non-linearity, and averaging. Efficientnet-B0 is a type of deep convolutional neural network that has been optimized for efficient use of computational resources while maintaining high accuracy. The ECG signals are first decomposed using wavelet scattering, which creates a multiresolution representation of the signal. The resulting coefficients are then fed into an efficientnetb0 neural network, which learns to extract features from the coefficients that are relevant for arrhythmia detection. By applying the properties of deep learning and wavelet scattering, it is possible to detect arrhythmias at an earlier stage, improving patient treatment outcomes. This method may improve the accuracy and speed of detecting arrhythmia compared to traditional ways.

2. LITERATURE SURVEY

2.1 Employing wavelet scattering and machine learning techniques to analyze ECG signals for the interpretation of emotions.

Using technology to sense and understand people's emotions can make using computers and other systems a better experience. The machines can react and adjust based on how the person is feeling. This technology can be used for many different things in entertainment and health care. In previous research, various machine learning techniques and inputs like sound, sight, or body signals were tested. This recently became popular because sometimes it's not possible to record audio or video for certain uses. So, it is important to create computer systems that can understand our emotions without needing to intrusively measure our physical functions The brain wave signals called electroencephalogram (EEG) are usually used to recognize things with a great amount of accuracy. Recent studies have found that ECG signals can be used for this [5]. EEGs can be measured, but it can be difficult to do it without getting in the way of daily tasks. The wavelet transform is being used in this study to analyze signal data and improve how well emotions can be recognized from ECG signals. In simple words, the wavelet scattering approach is a method used to get important information from ECG signals in the AMIGOS database. This approach helps us understand the signals at different time intervals. After analyzing the signals, we use different methods to evaluate how well they perform.

2.2 Classifying abnormal heart rhythms using pre-trained convolutional neural networks with 2D feature extraction.

A special kind of computer network called a deep neural network has been taught using a lot of information. It has been shown that this network is better at identifying irregular heartbeats than doctors who specialize in heart conditions. This is because of new improvements in a type of computer learning called deep learning. A circuit is a closed path or loop where electricity can flow. In the past, feature extraction was seen as an important part of identifying patterns in ECGs [6]. However, recent studies have shown that deep neural networks can directly extract features from the data. Doing independent research becomes difficult when deep neural networks are used because a lot of training data is required for them to work well and find the important details. New advancements in deep learning have shown that a computer system, called a deep neural network, can learn to identify irregular heart rhythms (arrhythmias) more accurately than doctors specialized in heart conditions. This is achieved by training the computer system with large amounts of data. A circuit is a path or loop that allows electricity to flow. It is made up of various components, such as wires, switches, and electrical devices. When a circuit is complete, meaning it is connected in a continuous loop, electricity can flow through it and power the devices connected to it. Moreover, in the past, it was believed that feature extraction was important for identifying patterns in ECG. However, recent studies have shown that deep neural networks can do feature extraction directly from the data. It is difficult to do research on your own because deep neural networks require a large amount of training data to work accurately and find details.

2.3 A new way of using deep learning to quickly identify heartbeats in real-time ECG signals.

The electrocardiogram (ECG)-based early detection of heart problems is discussed in this article along with a novel, personalized combination strategy. An ECG is a bioelectric signal that assists in observing the electrical activity of the heart. The normal and pathological physiology of the heart can be revealed, as well as health information. In order to prevent stroke or sudden cardiac death, it is crucial for heart patients to have an early diagnosis of cardiac abnormalities. This article's primary goal is to identify significant heartbeats that could harm the organ's health. Heart rate segmentation comes after feature point identification by the modified Pan-Tompkin technique. An additional hybrid deep convolutional neural network (CNN) [7] is then put forth for testing using conventional and real-time long-term ECG data. The extra ventricular rhythm (SVE), ventricular rhythm (VE), intraventricular conduction disturbance (IVCD), and normal rhythm (N) were all effectively assigned to a variety of aberrant cardiac rhythms in this study.

2.4 A new method using a combination of BiGRU-BiLSTM and multi-layered dilated CNN is developed to detect abnormal heart rhythms.

In particular, heart rhythm categorization and arrhythmia identification using deep learning approaches has made early strides in the processing of complex electrocardiographic information. But there is still a lot of progress needed in the field of health data analysis. This study [8] introduces a new approach for classifying cardiac arrhythmia. It is called dual structured bidirectional recurrent neural network (RNN). This new approach aims to solve problems with multilayer convolutional neural network (CNN) models. Initial preprocessing of the data does not employ statistical features and instead uses a faster Type II Chequashev filter. Utilizing Daubechies wavelengths, which are capable of resolving signal distortion and discontinuity issues, the preprocessing filter's noise is also removed.

The Pan-Tompkin normalization approach is then used to perform Z normalization in order to handle various normal distribution sample types. The signal is finally rebuilt to deal with the unbalanced signal class using a composite signal based on the Creative Adversarial Network (GAN). The two-way closed regression unit, BiGRU, and two-way long-term memory, BiLSTM) [9] of the proposed two-way RNN with extended CNN (BRDC) appears to use the potential of multilayer extended CNN and two-way RNN unit to build merge features. Finally, the rectified linear unit (ReLU) trigger function is achieved and the layer-classified signals are fully coupled. The proposed model is created and tested using information from the 2017 Physio Net Challenge. The performance and understandability of the learned model improve a lot when we combine the merged features with the expanded CNN. The study showed that the new BRDC model is better than other models in diagnosing arrhythmias. It had very high accuracy and recall rates of 99. 90%, 98.41%, and 97.96% during training with ECG data from MIT-BIH. The method we suggest can significantly reduce the time it takes to use RNNs with multilayer extended CNNs. This is one of the main discoveries of our study.

2.5 Making heart disease risk predictions more accurate by using a combination of classification techniques.

Data science uses machine learning, which is connected to artificial intelligence, to address a variety of issues. Predicting results based on historical data is a frequent use for machine learning [10]. When predicting results, the computer first applies patterns it has learned to an unknown data set. An effective machine learning method for prediction is classification. While some categorization algorithms are reasonably accurate in their predictions, others are not. This article examines a technique known as set classifier, which enhances the precision of weak algorithms by mixing various classifiers. The dataset for heart disease was used for experiments using this tool. For the purpose of figuring out how to use the aggregation technique to increase the accuracy of heart disease. To show how the algorithm can help detect diseases at an advanced stage, this paper goes beyond only making weak classifier algorithms more accurate. The beginning the research shows that combining weak classifiers using encapsulation and augmentation techniques can improve how well they predict the risk of heart disease. Synchronous classifiers have been used to make weak classifiers more accurate by up to 7%. With feature selection in place, the process operates more efficiently and more accurately, as evidenced by the outcomes.

3. MATERIAL AND METHODS

Arrhythmia is a condition where the heart beats irregularly, too fast, or too slow. It can be caused by various factors such as heart disease, high blood pressure, or electrolyte imbalances. Arrhythmia detection is a critical task in the field of cardiology as it can lead to serious health issues if not treated in time. Lately, researchers have been using computer programs to analyze electrical signals from the heart (ECG) and identify abnormal heart rhythms. Wavelet scattering is a feature extraction method that decomposes a signal into its constituent parts, allowing for more precise analysis. It has three layers namely, convolution, non-linearity, and averaging. Wavelet scattering can provide a compact representation of ECG signals that can capture important features such as QRS complexes, P-waves, and T-waves. Convolutional neural networks (CNNs) belonging to the Efficient Net family are intended to perform at the highest level while using less computational resources. The smallest and fastest model in the family, EfficientNetB0, makes it ideal for real-time applications like arrhythmia detection. The combination of wavelet scattering and EfficientNetB0 has shown promising results for arrhythmia detection. The wavelet scattering technique can extract important features from ECG signals, while the EfficientNetB0 model can classify the features into different arrhythmia classes. In summary, the combination of wavelet scattering and EfficientNetB0 is a promising approach for arrhythmia detection using ECG signals. It might enhance arrhythmia detection's precision and effectiveness, which could aid in early detection and treatment. In this research work, we used three different ECG datasets. One dataset is called ARR and comes from the MITBIH arrhythmia database. The second dataset is called CHF and comes from the BIDMIC congestive heart failure database. The last dataset is called NSR and comes from the MIT-BIH normal sinus rhythm database.

3.1 Block Diagram

The block diagram of proposed work is shown in figure 1. Initially the raw input ECG signal from various databases is collected. Preprocessing and feature extraction takes place in the input ECG Training Data. After this wavelet scattering Algorithm is applied to extract the dominant features in ECG signal. The obtained features are then converted in to scalogram using continuous wavelet transform. Finally, the ECG images are classified using various deep learning models and the results are compared with other state of art models.

3.2 ECG Preprocessing and Feature Extraction

In the study of electrocardiogram (ECG) signal, preprocessing and feature extraction are crucial procedures. To increase the accuracy of subsequent analysis, preprocessing cleans out noise and spuriousness from the ECG signal. Several methods, including baseline bias removal, and artefact removal (e.g., transitions), can be used to do this. electromotor and electrode). The process of taking pertinent data out of an ECG signal is called feature extraction. This often entails recognising and measuring a few of the ECG waveform's essential components, including the QRS complex's length and amplitude, P wave and T wave lengths, and heart rate. Diagnoses for arrhythmias, myocardial infarction, and heart failure can all be made using these criteria. A model can be trained to recognise patterns in ECG waveforms, and relevant features can then be automatically extracted. Machine learning techniques can also be utilised for feature extraction. Preprocessing and feature extraction are crucial phases in ECG analysis generally because they enable precise diagnosis and monitoring of heart condition.

3.3 Wavelet Scattering Algorithm

For intense use in machine learning and machine learning, wavelet scattering networks enable you to create low-disparity features from time series and real-value image data with little setup. Entities are continuous to distortions and insensitive to translations of the input on an invariant scale that you designate. Entities are not affected by rotations in the 2-D scenario. Scaling filters and predetermined wavelengths are employed by the broadcast network. Mallet was a pioneer in developing a mathematical framework for investigating convolutional neural architectures, along with Bruna and Anden. The wavelet scattering of 1-D signals has been effectively modelled by methods created by Anden and Lostanlen. Oyallon has created effective 2D broadcasting algorithms. The major developers of the ScatNet and Kymatio software for computing diffusion transforms are Anden, Lostanlen, and Oyallon. Three characteristics that deep learning architectures have have been outlined by Mallet and others as being necessary to extract relevant features from data

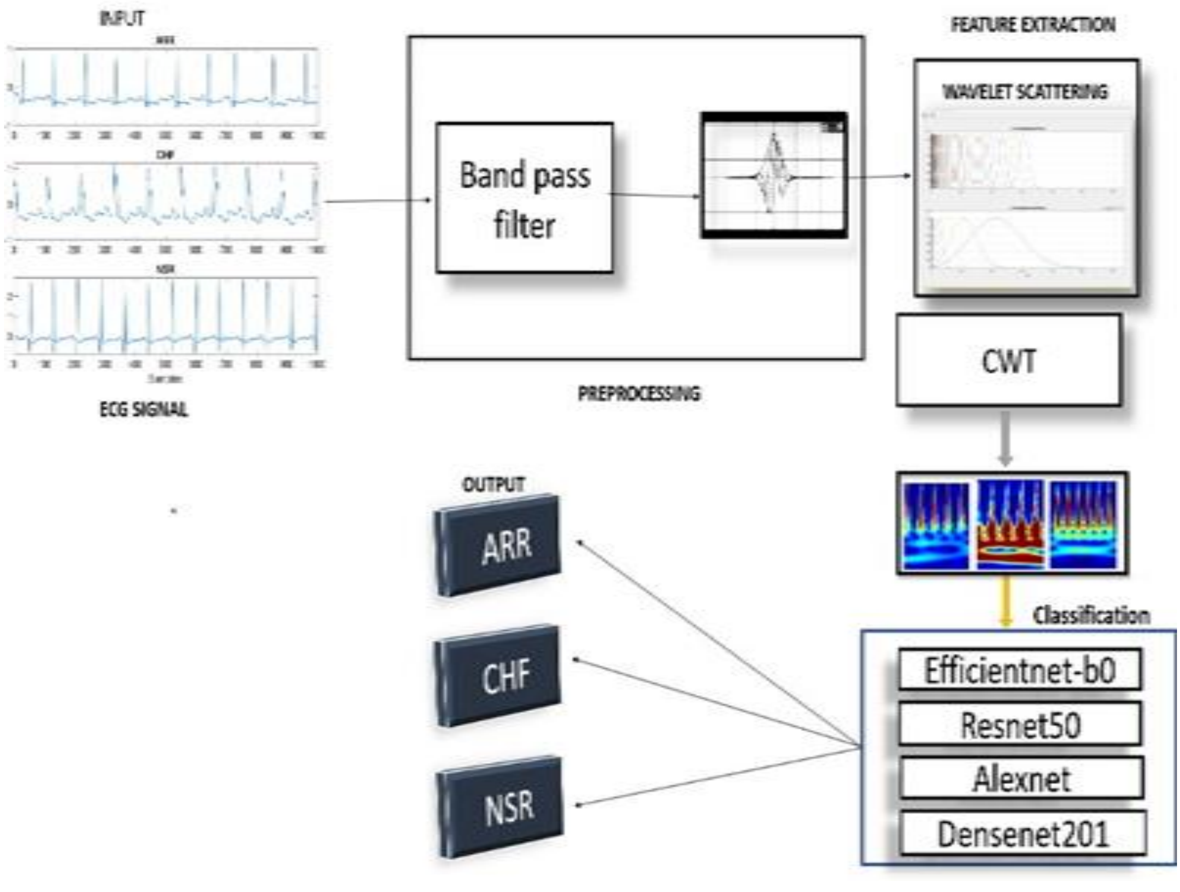

Figure 1: Block Diagram for Proposed System

- Contraction on several scales
- Hierarchical symmetries linearized
- Inconsistent performance

All of these characteristics are present in the wavelet scattering network [11-13]. By dividing the fluctuations on various scales, the wavelet transform linearizes minor aberrations like expansion. The wavelet transform also offers a sparse representation for many natural signals. The diffuse transform generates data representations that minimize differences within a layer while keeping the capacity to differentiate across classes by combining wavelet transformations with the other diffuse network properties discussed below. Broadcast transform networks and deep learning transform networks differ significantly in that the filters are specified rather than learned. You can frequently utilise Diffusion successfully in cases where there isn't enough training data because a Diffusion transformation is not necessary to learn the filter responses. **Continuous Wavelet Transform**

With the help of Continuous Wavelet Transform (CWT), non-stationary signals, such as electrocardiogram signals, can extract their features. The foundation of CWT is the idea of wavelets, which are functions localized in the time and frequency domains. Here are some actions you can take to use CWT to detect arrhythmias. To group things in a better way, we use a method called CWT to change a particular type of signal called 1D ECG into a different kind of image called a 2D scalogram. In easier terms, CWT can help find irregular heartbeats and is a useful tool for detecting arrhythmia. It can accurately explain the signal and record the changing frequency of the ECG signal. However, you must select the wavelets and hyper parameters of the algorithm with caution.

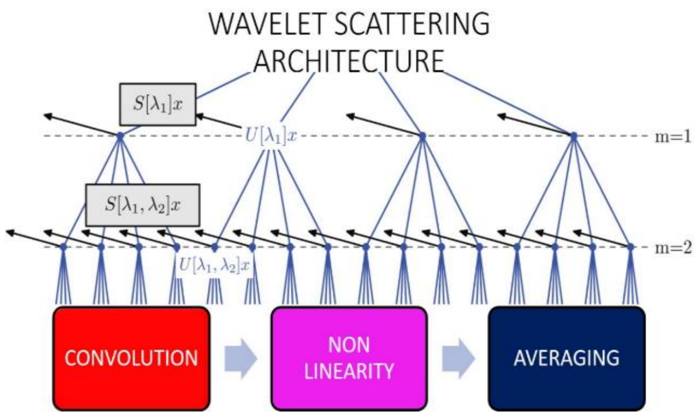

Figure 2: Architecture of Wavelet Scattering Algorithm

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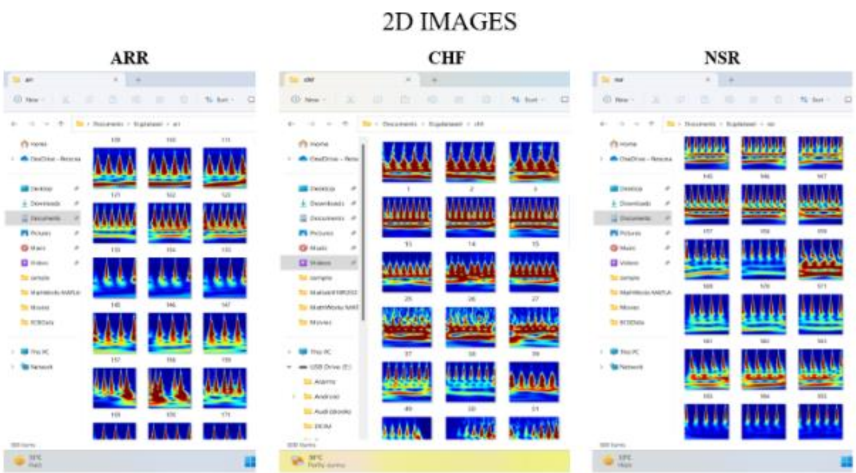

Figure 3: Scalogram for ARR, CHF, and NSR

3.4 Classification Models

For automatic classification of cardiac arrhythmia various ML and DL methods are implemented [14-16]. In our proposed work EfficientNet B0 is used and compared with three different models. The later part gives the detail explanation of each model.

3.4.1 EfficientNet B0

It is a type of convolutional neural network that uses multiplexing blocks. It scales all dimensions of depth, breadth, and resolution uniformly by using a specific architecture and scaling approach.

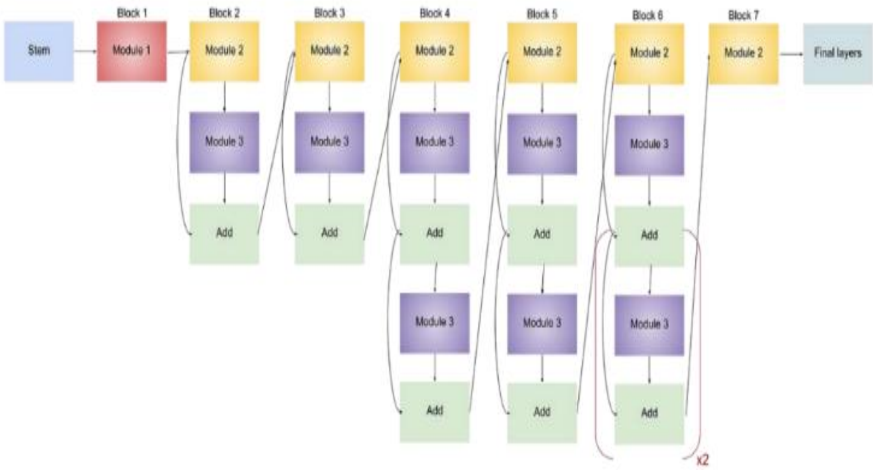

Figure 4: Architecture of Efficientnet B0

3.4.2 ResNet-50

50 layers make up the deep neural network design known as ResNet-50. It resolves the ensuing gradient problem using the remaining blocks. The network can learn residual mappings that are simple to optimise thanks to residual blocks. A pre-trained model on a sizable data set, such as ImageNet, can be utilised with ResNet-50 for transformation learning. On the ECG dataset, pre-trained weights can be used as a starting point for training, which can significantly save training time and increase model accuracy. ResNet50's performance on the ECG dataset can be enhanced with adjustments. The final layers of ResNet-50 are changed during the refining process to new layers tailored to the ECG data set. The complete network is then low-learning-rate trained on the ECG dataset. In conclusion, by utilising transformation and fine-tuning learning, ResNet-50 can be utilised as a feature extraction method in arrhythmia identification. It is an effective deep learning architecture that can separate out high-level characteristics from ECG data, considerably enhancing classification accuracy. To get the best results, it is crucial to preprocess the data and make cautious hyperparameter selections.

3.4.3 Alexnet

There are eight learnable classes in Alexnet. With the exception of the output layer, each of the model's five layers—which have a maximum composite combination of three layers each—uses Relu activation. They discovered that utilising relu as the trigger accelerated training by nearly six times. Additionally, they employ suppression classes to prevent overfitting in their model. The Imagenet dataset is also used to train the model. Nearly 14 million photos in a thousand layers make up the Imagenet collection.

3.4.4 DenseNet-201

There are 201 layers in this convolutional neural network. The trained network can classify images into 1000 different types of objects, including various animals, mice, keyboards, and pencils. As a result, the network restored detailed representations of features for a variety of images. The network can accept images up to 224 x 224.

4. SIMULATION

The Proposed system is simulated using MATLAB version 2023a software. The Language used here is c/c++. The software specifications are need to be installed, so that we can continue the simulation. The specifications that are need to be installed:

- Deep learning toolbox
- Computer vision toolbox
- Efficientnet-b0 model, Resnet50, Alexnet and Densenet201 in deep neural network

The simulation outputs are shown below:

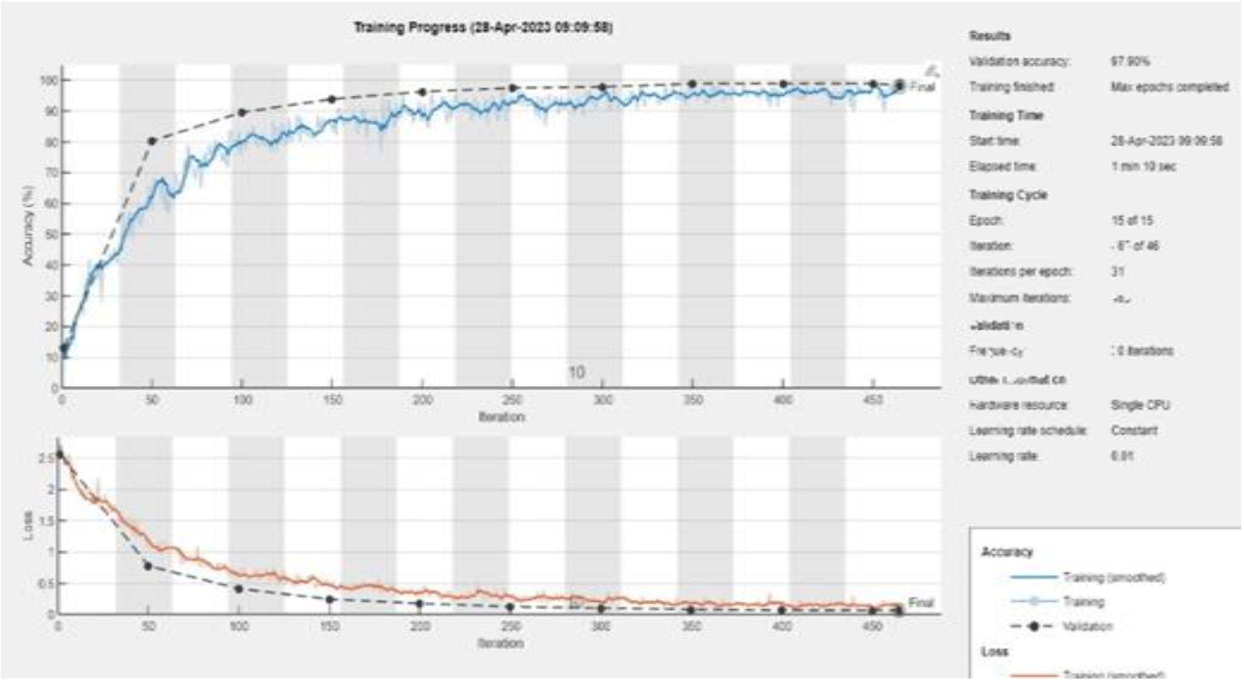

Figure 5: Simulation output for Efficientnet-b0

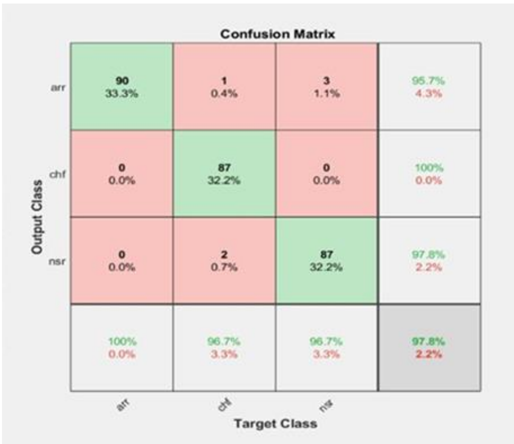

Figure 6: Confusion matrix for Efficientnet-b0

5. RESULT AND DISCUSSION

The performance of our approach gave better accuracy compared with different models that are shown below in table 1.

Table 1: Comparison of accuracy and training time with other models

Models	Accuracy (%)	Elapsed Time (hours)
ALEXNET	86.67	0.3

RESNET50	97.78	1
DENSENET201	89.26	1.5
EFFICIENNET-BO (PROPOSED)	**97.9**	**0.7**

The pre-trained models have been assessed for how well they perform using measures such as accuracy, precision, recall, specificity, and f1 score. It is shown in figure 2.

Table 2: Comparison of performance metrics with other models

Models	Accuracy(%)	Precision(%)	Recall(%)	Specificity(%)	F1 Score(%)
ALEXNET	86.67	86.4	86.6	87	86.46
RESNET50	97.78	96.6	97.3	96.9	96.94
DENSENET201	89.26	88.1	88.67	88.95	88.38
EFFICIENNET-BO (PROPOSED)	**97.9**	**97.7**	**97.8**	**97.7**	**97.74**

a) Alexnet b) Densenet201

c) Resnet50

Figure 7 (a-c): Confusion matrix for Alexnet, Densenet-201, and Resenet-50

6. CONCLUSION

In conclusion, using wavelet scattering and EfficientNetB0 can be a promising approach for arrhythmia detection. By combining wavelet scattering with deep learning techniques, we can extract more informative features from ECG signals, which can improve the accuracy of arrhythmia classification.

6.1 FUTURE SCOPE

There is room for future enhancement in this approach. One possible path to consider is to study other types of deep learning models, like recurrent neural networks (RNNs) or transformer models, that can understand connections over time in ECG signals. Another direction is to investigate the use of transfer learning, where pre-trained models on large datasets are fine-tuned for arrhythmia detection. This can help to improve the generalization and robustness of the models. Additionally, it is crucial to test the proposed approach using bigger and more varied data sets, including data from various age, sex, and ethnic groups. This can enhance the model's clinical value by validating the model's performance in an actual clinical environment. In general, wavelet scattering and EfficientNetB0 provide a solution for automated arrhythmia detection that has the potential to increase diagnostic precision and patient outcomes.

AUTHOR'S CONTRIBUTION

R.Anandha Praba: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization.
L.Suganthi: Investigation, Supervision, Writing - Review & Editing, Resources.
E.S.Selva Priya: Formal analysis, Writing- Reviewing and Editing.
G. Shakthi: Validation, Investigation, Writing - Reviewing and Editing

FINANCIAL SUPPORT AND SPONSERSHIP

The present research work was not funded by any funding agency.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable

CONFLICTS OF INTEREST

The authors reveal no conflicts of interest concerning the work reported in this article.

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