

Classification of ECG signals using deep neural networks

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Abstract

The electrocardiogram (ECG) is an essential tool in the field of cardiology, as it enables the electrical activity of the heart to be measured. It involves placing electrodes on the patient's skin, facilitating the measurement and analysis of cardiac rhythms. This non-invasive and painless test provides essential information about the heart's function and helps in diagnosing various cardiac conditions. The classification of ECG signals using deep learning techniques has garnered substantial interest in recent years; ECG classification tasks have exhibited promising outcomes with the application of deep learning models, particularly convolutional neural networks (CNNs). The GoogleNet, AlexNet, and ResNet Deep-CNN models are proposed in this study as reliable methods for accurately diagnosing and classifying cardiac diseases using ECG data. The primary objective of these models is to predict and classify prevalent cardiac ailments, encompassing arrhythmia (ARR), congestive heart failure (CHF), and normal sinus rhythm (NSR). To achieve this classification, 2D Scalogram images obtained through the continuous wavelet transform (CWT) are utilized as input for the models. The study's findings demonstrate that the GoogleNet, AlexNet and Resnet models achieve an impressive accuracy rate of 96%, 95,33% and 92,66%, in accurately predicting and classifying ECG signals associated with these cardiac conditions, respectively. Overall, the integration of deep learning techniques, such as the GoogleNet, AlexNet, and ResNet models, in ECG analysis holds promise for enhancing the accuracy and efficiency of diagnosing and classifying cardiac diseases, potentially leading to improved patient care and outcomes.

Keywords: Electrocardiogram (ECG). Convolutional Neural Network (CNN). Normal Sinus Rhythm (NSR). Arrhythmia (ARR). Congestive Heart Fail (CHF).

1. Introduction

Heart diseases comprise a wide range of conditions that affect both the heart and the blood vessels. Some common examples of these conditions include coronary heart disease, stroke, heart failure, and cardiac arrhythmias. These conditions can have significant impacts on the cardiovascular system and overall heart health. Based on data provided by the World Health Organization (WHO), these diseases account for approximately 31% of global fatalities, positioning them among the primary causes of death globally. Hence, it is imperative to establish preventive measures, early diagnostic strategies, and effective treatments to mitigate the impact of these diseases on public health (Rajamhoana *et al.*, 2018; Ahsan *et al.*, 2022). Congestive heart failure (CHF) is a severe and critical cardiac condition that significantly contributes to mortality rates on a global scale. It occurs when the heart becomes incapable of pumping a sufficient amount of blood to maintain blood flow and meet the oxygen and metabolic demands of body tissues. The prevalence of CHF is staggering, with over 26 million adults worldwide suffering from the condition, and the number increasing by 3.6 million cases annually. Detecting CHF at an early stage plays a crucial role in improving treatment options and slowing down its progression. Timely identification allows for the implementation of appropriate therapeutic measures that can alleviate symptoms, enhance quality of life, and potentially improve long-term outcomes (Jahmunah *et al.*, 2019; Naik Jahmunah *et al.* 2021; Dalia *et al.* 2021). Arrhythmia (ARR) is another notable cardiac disorder that is linked to substantial morbidity and the risk of sudden death. Arrhythmia refers to an abnormal heart rhythm characterized by irregular heartbeats (Moghadas *et al.* 2020; Behar *et al.*, 2019; Pavel *et al.*, 2019). On the other hand, a normal sinus rhythm (NSR) indicates the proper propagation of electrical signals from the sinus nodes, serving as an indication of a healthy cardiac rhythm (Faust *et al.* 2021; Carrara *et al.*, 2015). Understanding the different cardiac conditions, such as CHF and Arrhythmia, is of utmost importance in the field of cardiology. Accurate diagnosis and classification of these conditions, including distinguishing NSR from abnormal rhythms, are crucial for guiding appropriate treatment strategies and reducing adverse cardiac events. Such advancements contribute to the development of personalized treatment plans and enhanced patient outcomes in the realm of cardiac care (Çınarc *et al.* 2021; Chenv *et al.* 2022; Nahak *et al.* 2020). The electrocardiogram (ECG) is a widely used diagnostic test that offers valuable insights into heart function by capturing and analyzing the electrical signals generated by the heart muscles. This non-invasive procedure has proven to be highly effective in providing cardiologists with comprehensive information about the presence and nature of cardiac pathologies. By assessing the electrical activity patterns of the heart, the ECG serves as a reliable tool for the early detection, diagnosis, and monitoring of a wide range of cardiac disorders, including but not limited to arrhythmias, myocardial infarction, conduction abnormalities, and structural abnormalities. Identification and rapid intervention of cardiac disorders play a crucial role in minimizing complications and improving clinical results. However, the interpretation of ECG signals can be subjective and dependent on the Cardiology specialist, which can lead to variations in results. It is possible to exploit the advantages of artificial intelligence and machine learning to improve the accuracy and reliability of cardiac disorders diagnosis. Advances in medical technology, including electrocardiography (ECG) and deep learning algorithms, have shown promise in improving the accuracy and efficiency of identifying and managing these cardiac disorders. Recent advancements in machine learning, specifically convolutional neural networks (CNNs), have the potential to play a pivotal role in this context. CNNs are machine learning models specifically designed for image analysis and have proven highly effective in classifying and detecting objects in complex images. This is why the use of popular machine learning models, namely GoogLeNet, AlexNet, and ResNet, for automatic detection and classification of cardiac disorder from ECG signals. Many authors have used deep learning for automatic identification and classification of ECG, the author in (Atal *et al.* 2020; Yıldırım *et al.* 2018) has improved the classification of arrhythmias using electrocardiogram (ECG) signals through the use of deep convolutional neural networks (CNNs) supported by optimization techniques. The paper (Olanrewaju *et al.* 2021) presents an advancement in the detection of arrhythmia and congestive heart failure using a combination of continuous wavelet transform and a

deep convolutional neural network (CNN) model called AlexNet. This approach utilizes the continuous wavelet transform to extract relevant features from ECG signals and employs deep neural networks for accurate classification. By combining these techniques, the classification of ECG signals becomes a powerful tool for detecting arrhythmia and congestive heart failure, facilitating timely diagnosis and targeted treatment interventions in the field of cardiology. In their paper (Çınarc *et al.* 2021), The authors of the paper have introduced a novel architecture that combines LSTM (Long Short-Term Memory) and a hybrid AlexNet-SVM model for the classification of ECG signals into three categories: normal sinus rhythm, abnormal arrhythmia, and congestive heart failure. This architecture aims to enhance the accuracy and effectiveness of ECG signal classification in differentiating between these cardiac conditions. In our study, we will explore the effectiveness of deep convolutional neural networks (deep-CNN) utilizing three specific models (GoogLeNet, AlexNet, and ResNet) for the automated detection of arrhythmia (ARR), congestive heart failure (CHF), and normal sinus rhythm (NSR) using ECG signals. By investigating the performance of these deep-CNN models, we aim to assess their potential in accurately identifying and classifying these cardiac conditions, thereby contributing to advancements in the field of ECG-based diagnostics. Google Net is a deep model distinguished by its innovative architecture based on inception blocks (Aswathy *et al.* 2018; Sekhar *et al.* 2021), Alex Net, meanwhile, is a pioneering model in the CNN field. Although it has a shallower architecture than GoogLeNet and ResNet, it has demonstrated its ability to extract discriminating features from complex images. Finally, ResNet is a revolutionary model that introduced residual connections. By exploiting the specific advantages of each model, we hope to deliver promising results and contribute to improving the detect of heart disease from ECG signals, which could have a significant impact on patient management and reducing diagnostic errors.

The methodology employed in this dissertation can be summarized through the following steps: Section two provides a comprehensive description of our methodology for the classification of ECG signals, offering detailed insights into the approach we have adopted. The classification process will be presented, outlining the various steps involved in the methodology. Section three delves into the utilization of transfer learning on three deep convolutional neural network (CNN) models, specifically GoogLeNet, AlexNet, and ResNet, with the aim of customizing them for our classification task. Furthermore, section four entails a comprehensive examination and evaluation of a classification study using these three deep CNN models, including the assessment of performance criteria. Lastly, in section five, we present our conclusions derived from the findings and contributions of this paper, synthesizing the key insights obtained throughout the study.

2. Methodology

This section offers a thorough and detailed description of the strategic approaches that have been proposed. and their underlying assumptions, the procedures used to classify ECG signals that have been confirmed as ARR, CHF, or NSR, the database used during the activity was described, as were the techniques used to carry out the tests and analyses. To achieve the goal of ECG signal classification using Deep Learning, the following methodology was used:

2.1 Data collection

For our study, we have utilized three distinct categories of ECG signals. to model a deep convolutional neural network (deep CNN): Cardiac arrhythmia (ARR); Congestive heart failure (CHF), and Normal sinus rhythm (NSR). Figure 1 provides an illustration of these three categories.

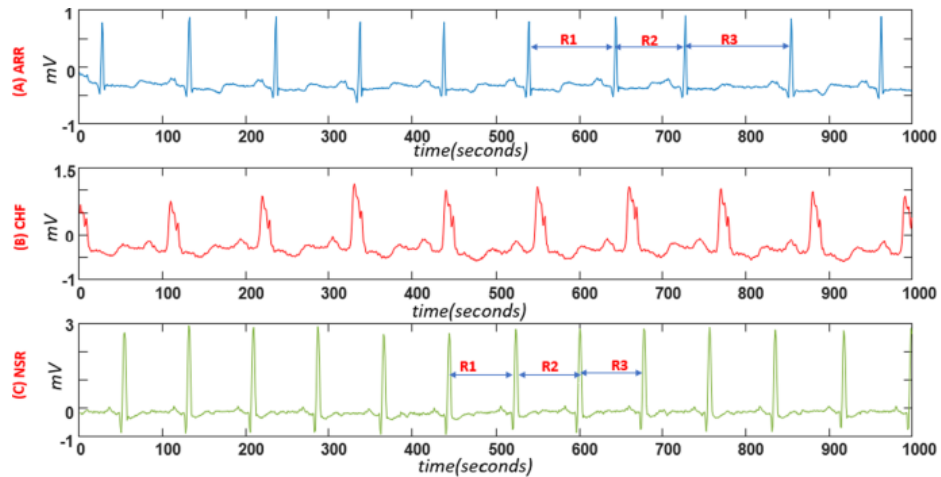


Figure 1 - ECG signals categorized into three types: a) ARR, b) CHF, and c) NSR.

These signals were acquired from 162 ECG recordings sourced from three Physionet databases. These databases encompass the following:

- The MIT-BIH arrhythmia database, which consists of 96 recordings of ARR signals.
- The MIT-BIH normal sinus rhythm database, which comprises 30 records of NSR signals.
- The BIDMC congestive heart failure database, which includes 36 records of CHF signals.

2.2 Data pre-processing

The data matrix has dimensions of 162 x 65536, indicating that it encompasses a total of 162 ECG signals. Each ECG signal in the matrix is composed of 65536 samples. These signals have been accurately labeled, providing information about their respective types. Specifically, lines 1 to 96 in the database represent ARR signals, lines 97 to 126 correspond to CHF signals, and lines 127 to 162 correspond to NSR signals.

To address our specific problem, data pre-processing begins at the database level. Each individual record, with a length of 65536 samples, is segmented into smaller signals of 500 samples to increase the database size and make it suitable for training a convolutional neural network, such as GoogleNet. Additionally, to ensure a balanced distribution, we select 30 recordings of each type (ARR, CHF, and NSR). Each recording is further divided into 10 chunks, each consisting of 500 samples. As a result, we obtain 300 records (30 recordings x 10 chunks) of each category, yielding a total of 900 records in 500-sample segments (Olanrewaju *et al.* 2021).

2.2.1 Conversion of ECG signals into images using the continuous wavelet transform (CWT)

We aim to convert one-dimensional ECG signals into two-dimensional RGB images by extracting frequency-specific features using continuous wavelet transform. The resulting images, obtained through time-frequency representation, serve as inputs to the GoogleNet deep CNN model. Each ECG signal undergoes CWT, generating a cwt scalogram comprising all coefficients. These scalograms are transformed into 224x224 images using a 128-color jet-like color map and saved in separate folders for each signal category (ARR, NSR, and CHF). In total, we generate 900 scalogram images as a result of the data processing steps, with 300 images for each signal category, facilitating classification with models GoogleNet, AlexNet and ResNet. The selection of continuous wavelet transform (CWT) as our chosen method is driven by several compelling factors. Firstly, CWT enables the extraction of valuable and pertinent information from signals in the time domain. Unlike other signal processing techniques, CWT provides a flexible representation that captures both local and global characteristics of the signal. By applying wavelets with different scales and positions, the CWT allows for the analysis of signals at different resolutions, revealing fine details and variations that may be crucial for signal interpretation.

Moreover, CWT offers control over the waveform shape, which is advantageous for signal analysis. By manipulating the scale and translation parameters of the wavelet function, the CWT can be tailored to emphasize specific features or frequency components of interest. This adaptability makes CWT a powerful tool for signal processing tasks, including feature extraction and pattern recognition. The mathematical expression representing the CWT of a function $s(t)$ is defined as follows:

$$CWT(a, b) = \int x(t) \cdot \psi^* \left((t-b) / a \right) dt \quad (1)$$

In this equation, the scale parameter ' a ' regulates the width of the wavelet function, while the translation parameter ' b ' determines the position of the wavelet function along the time axis. The input signal is denoted by ' $x(t)$ ', and the complex conjugate of the wavelet function is represented by ' $\psi^* \left((t-b) / a \right)$ '.

The integral is taken over the entire range of t , indicating that the CWT is calculated for each possible value of the scale parameter a and the translation parameter b . The result is a two-dimensional representation of the signal's time-frequency content, where different values of a and b correspond to different scales and positions in the time-frequency plane.

By varying the values of a and b , the CWT captures the signal's spectral information at different resolutions, allowing for the detection of transient events and localized frequency components. This provides a valuable tool for analyzing time-varying signals such as ECG data, as it enables the extraction of relevant features and patterns for further classification and analysis.

The converted results of the three signal categories are displayed in Figure 2, representing the outcome of the conversion process conducted on all 900 signals within our database.

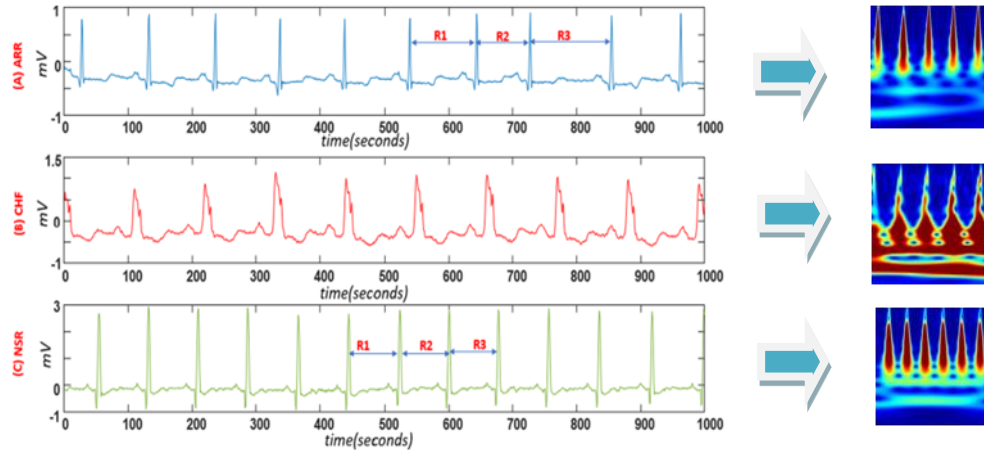


Figure 2 - Converting 1D ECG signals to the appropriate scalogram images.

Our data-base is partitioned into two distinct parts: one for training, which accounts for 80% of the data, and the other for testing, which constitutes 20% of the data (see figure 3).

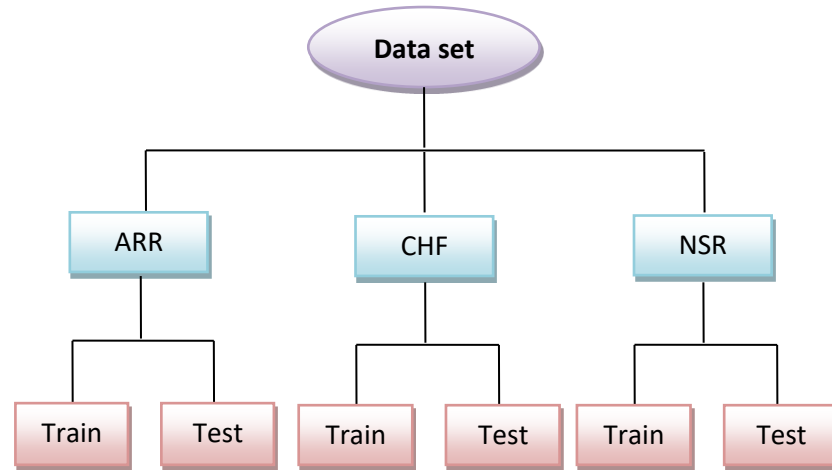


Figure 3- Basic data chart.

2.3 Model selection

Different CNN - Deep learning architectures, such as Googlenet, Alexnet, and RESNET, were examined and assessed to determine their efficacy in ECG signals classification. The selection of the optimal model took into consideration factors such as accuracy, computational efficiency, and compatibility with the dataset.

2.4 Model training

The selected model was trained using the pre-processed dataset. This involved supplying the model with images and optimizing its parameters through an iterative process called backpropagation. The training process aimed to enable the model to learn the distinctive features and patterns associated with pneumonia-infected lungs.

2.5 Model evaluation

The trained model was evaluated using a separate set of test images. Performance measures such as precision, recall and F1 score were calculated to assess the model's effectiveness in ECG signals classification.

2.6 Model enhancement

Based on the evaluation results, the model is refined and improved to optimize its performance. This may involve techniques such as fine-tuning, regularization or architectural modifications to achieve better accuracy and generalization.

2.7 Implementation

The revised model, demonstrating superior performance in pneumonia detection, has been implemented in future research. This could involve deploying the model in a real clinical environment, or integrating it into existing medical imaging systems.

By following this methodology, the goal of automated and accurate classification of ECG signals using deep learning techniques can be achieved, potentially contributing to improved health outcomes and saving lives.

3. Transfert Learning

Transfer learning is a machine learning approach that leverages knowledge acquired from solving one task to enhance performance on a different task. The underlying concept is that the general knowledge obtained from tackling one task can be effectively utilized to address another task that shares similarities or connections. Transfer learning can be achieved in a number of ways. For example, a pre-trained model can be used on a main task (such as image classification) and reused, adapting only the final layers for a specific task (such as object detection). In this way, the model benefits from the general knowledge learned during the main task and can specialize more quickly in the specific task. Transfer learning is a technique widely used in neural network models such as GoogLeNet, AlexNet and ResNet.

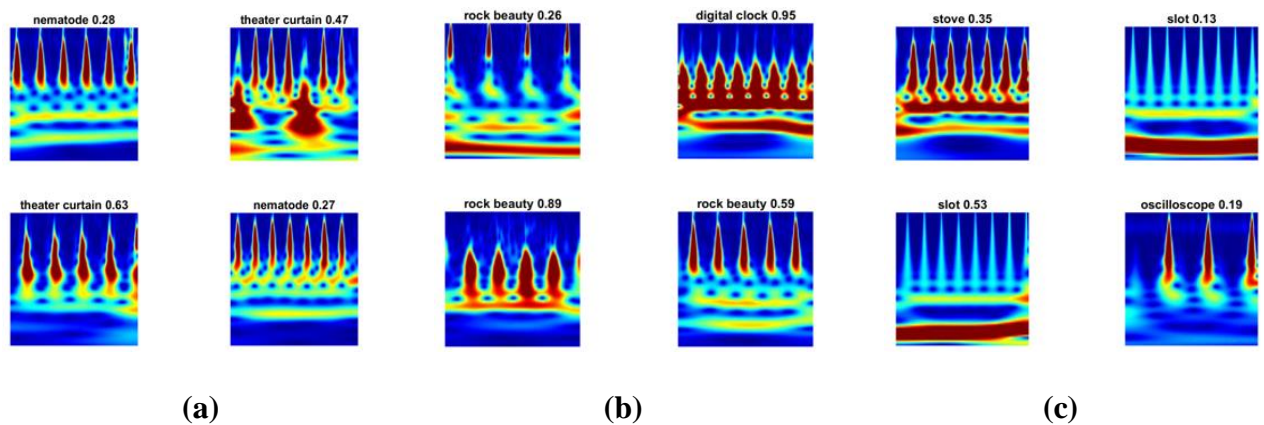
GoogLeNet is celebrated for its innovative architecture featuring inception modules that combine different filter sizes to extract features at different scales. In transfer learning with GoogLeNet, we can use a model pre-trained on a large image database (such as ImageNet) and adapt it to a specific task by modifying or re-training the last layers of the network for that task.

AlexNet was the first model to demonstrate the effectiveness of deep learning for computer vision. In transfer learning with AlexNet, we can also use a model pre-trained on ImageNet and adapt it to a specific task by adjusting the final layers or re-training them.

ResNet, or Residual Network, was introduced to solve the problem of performance degradation when adding extra layers to neural networks. ResNet's architecture includes residual connections to circumvent the problem of vanishing gradients. In transfer learning with ResNet, we can use a model pre-trained on large databases (such as ImageNet) and reuse it by adapting the last layers for a specific task.

In our work, we have used these three models, which have been pre-trained on an image database containing over a million images and capable of classifying images into 1,000 different object categories. This pre-training on such a large amount of data enables these models to acquire general knowledge about the representation of objects in images.

When we applied our three models without using transfer learning on our database, these models gave us the wrong results, as illustrated in figure 4, we entered the models with four random scalogram images, but at the output, we obtained erroneous classification.



**Figure 4- Image classification without using transfer learning with the a) GoogleNet
b) AlexNet c) ResNet.**

To classify ARR, CHF, and NSR in our spectrogram images, we modified the last layers of these three models as follows: we replaced the last three layers, for GoogleNet, {loss3-classifier; prob; output} by {fullyconnected; softmax; output}, for AlexNet: {fc8; prob; output} by {new_fc; prob; new_classout} and for ResnetNet: {fc1000; prob; ClassificationLayer_predictions} by {new_fc; prob; new_classout}, as shown in the three Figures 5, 6, and 7.

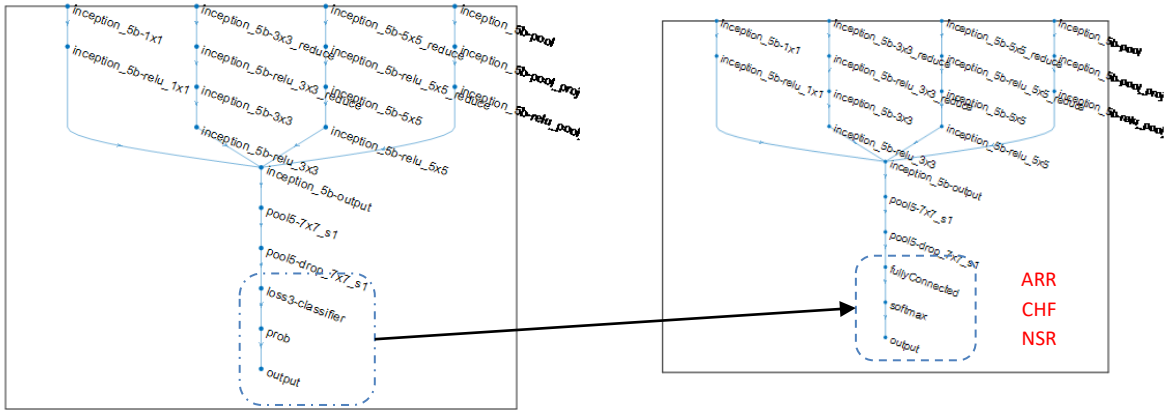


Figure 5- Modification of the last three GoogleNet layers.

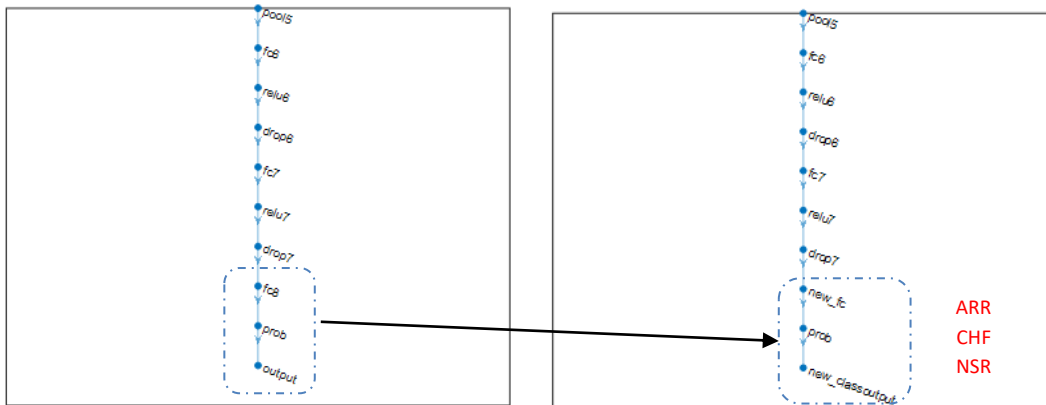


Figure 6- Modification of the last three AlexNet layers.

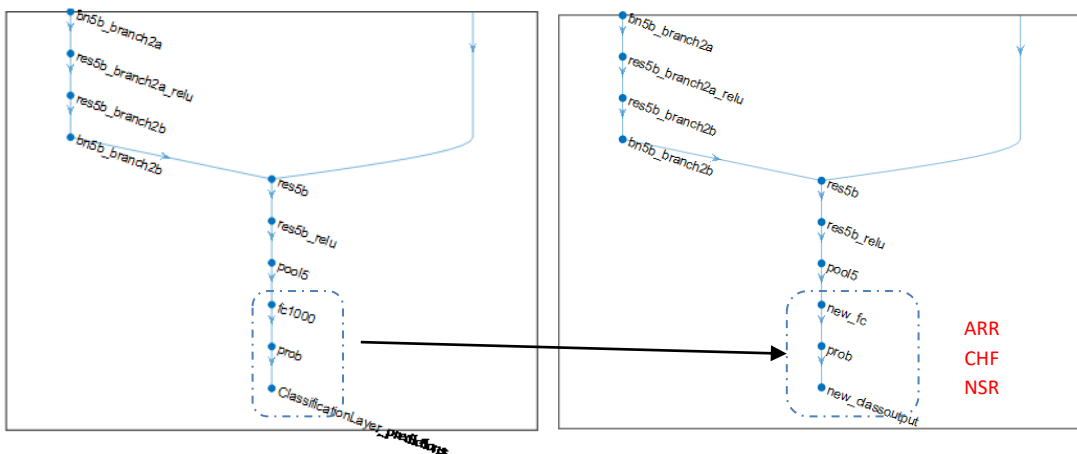


Figure 7- Modification of the last three ResNet layers.

4. Results and discussion

Results and discussion may vary depending on specific data, dataset quality, training parameters and other factors. The performance of the proposed model is assessed using various metrics, including Accuracy, Precision, F1 Score, and Recall, as detailed in Table 1.

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN) \quad (2)$$

$$\text{Recall} = TP/(TP + FN) \quad (3)$$

$$\text{Precision} = TP/(TP + FP) \quad (4)$$

$$\text{F1 - Score} = 2/((1/\text{Precision}) + (1/\text{Recall})) \quad (5)$$

Table 1 – Performance results of our models.

Model	Accuracy	TP	FN	Recall	FP	Precesion	F1-score
GoogleNet	0.96 (96%)	48	1	0.9796 (98%)	1	0.9796 (98%)	0.9796 (98%)
AlexNet	92.6667 (92.7%)	46	0	1 (100%)	0	1 (100%)	1 (100%)
ResNet	95.3333 (95.3%)	47	1	0.9792 (98%)	1	0.9792 (98%)	0.9792 (98%)

4.1 Results

Here are the results and discussion of the application of the GoogLeNet, AlexNet and ResNet models to the detection of pneumonia:

- GoogLeNet: The GoogLeNet model achieved an accuracy (accuracy: 0.96) of 96% for spectrogram images of ECG signals classification. Recall was 98% (Recall: 0.9796), indicating that the model correctly classified the majority of ARR, CHF and NSR. Precision was 98% (Precision: 0.9796), meaning that that, on average, approximately 98% of the positive predictions made for each class (ARR, CHF, and NSR) are correct. This indicates a high level of accuracy in identifying instances of each cardiac condition. The F1 score was 96% (F1 Score: 0.96081), indicating good harmony between precision and recall.

- ResNet: The ResNet model achieved an accuracy of 95.33% (Accuracy: 95.3333) for the classification of three cases. Recall was 98% (Recall: 0.9792), meaning that the model identified a large proportion of positive three cases (ARR, CHF and NSR). Precision was 98% (Precision: 0.9792), indicating that most positive cases were correctly identified. The F1 score was 98% (F1 Score: 0.9792), indicating a reasonably balanced performance between precision and recall.

- AlexNet: The AlexNet model achieved an accuracy of 92.67% (92.667) for the for the classification of three cases. Recall was 100% (1), indicating that the model successfully identified a large proportion of positive three cases (ARR, CHF and NSR). Precision was 100% (1), showing that all of the three cases identified as positive. The F1 score was 100% (1), suggesting good overall model performance.

As training iterations progress, model accuracy is measured and recorded. The graph of accuracy versus number of iterations for the GoogleNet model (Figure 8) shows how accuracy evolves as the model is trained. Initially, accuracy may be relatively low, but as the number of

iterations increases, the model learns to detect pneumonia better and accuracy gradually increases. This graph may show fluctuations, but overall, accuracy should increase until it reaches a plateau where it converges on a maximum value. Similarly to GoogLeNet, the graph of accuracy versus number of iterations for AlexNet (Figure 9) represents how accuracy evolves as the model is trained to detect pneumonia. Initially, accuracy may be low, but as training progresses, the model adjusts and accuracy improves. As with GoogLeNet, accuracy may fluctuate with each iteration, but should increase overall until it reaches a maximum value or stabilizes. For ResNet, the graph of accuracy versus number of iterations for ResNet (Figure 10) represents how accuracy evolves during training for pneumonia detection. As iterations progress, the ResNet model learns to better extract relevant features from the pneumonia image, leading to improved accuracy. Again, accuracy may vary during training, but should increase overall until it reaches a maximum value or stabilizes.

The confusion matrix is used to evaluate various measures of model performance, such as precision, recall, specificity and F1 score. These measures provide information on the model's ability to correctly classify samples from both classes.

It's important to note that the confusion matrix may be different for each model (GoogLeNet, AlexNet, ResNet) depending on their individual performance in detecting pneumonia. Extracting specific confusion matrices requires training and testing the models on specific data.

Figures 11, 12 and 13 show the confusion matrix obtained from our work.

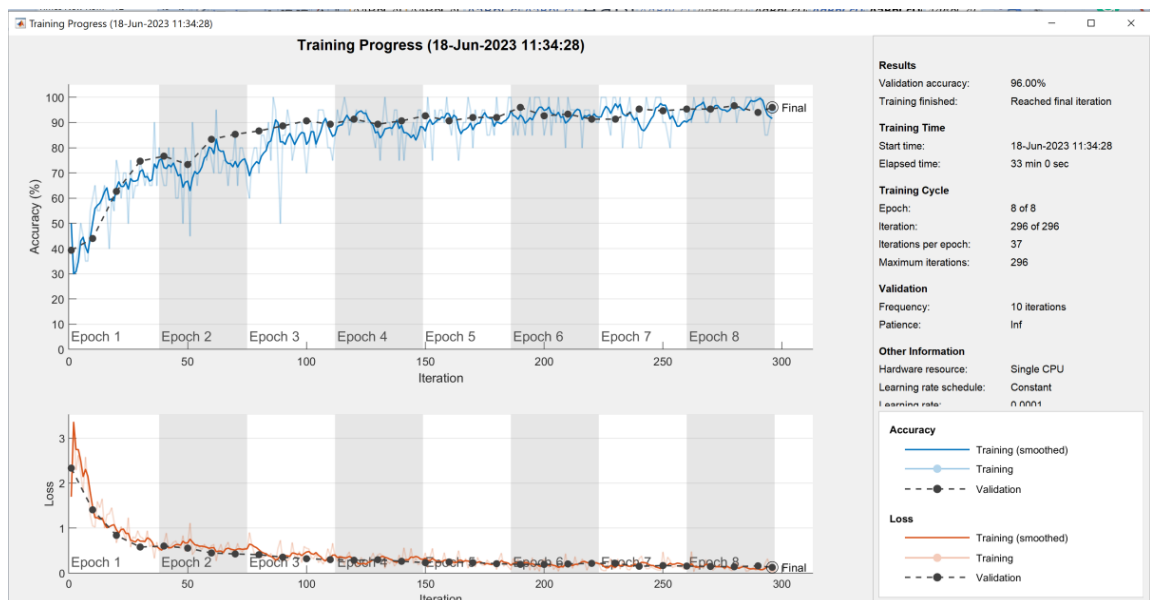


Figure 8- The figures show (a) Accuracy (%) as a function of the number of iterations and (b) Loss as a function of the number of iterations (GoogleNet).

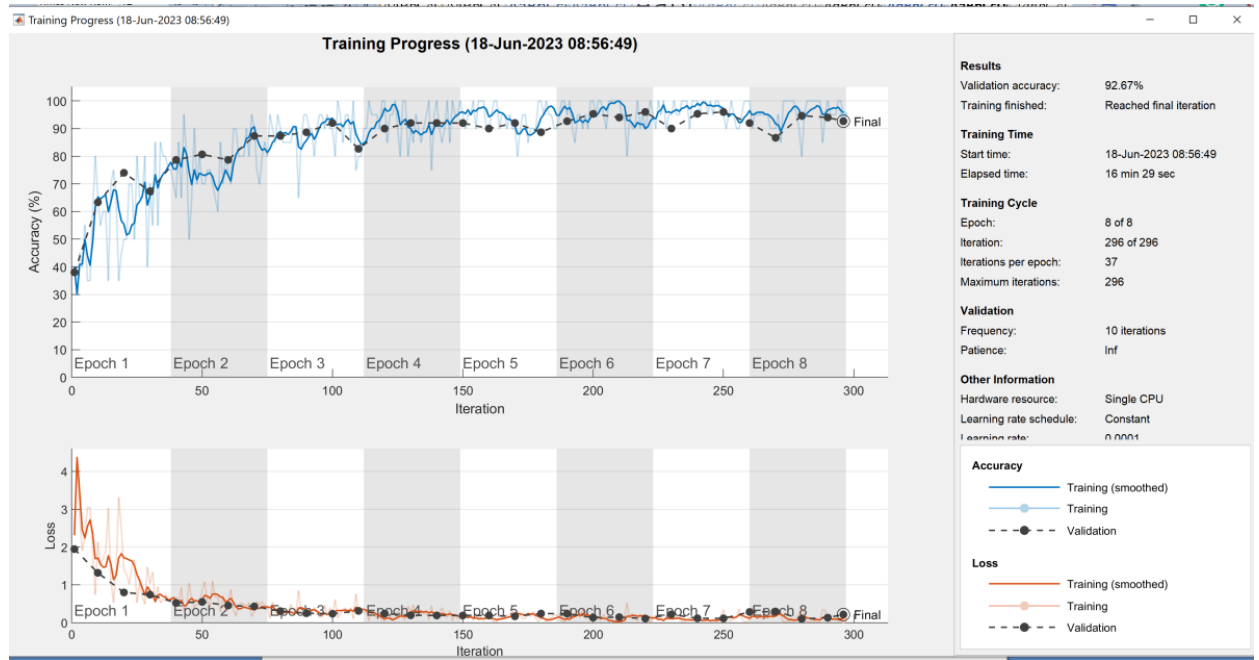


Figure 9- The figures show (a) Accuracy (%) as a function of the number of iterations and (b) Loss as a function of the number of iterations (AlexeNet).

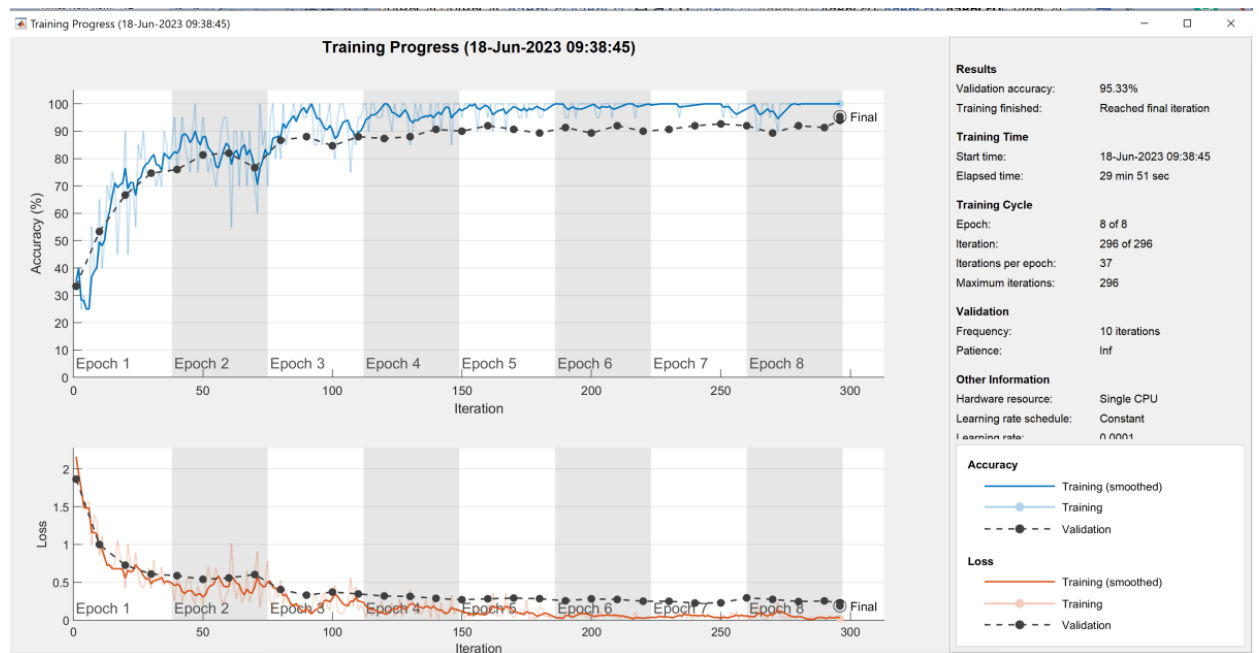


Figure 10- The figures show (a) Accuracy (%) as a function of the number of iterations and (b) Loss as a function of the number of iterations (ResNet).

Confusion Matrix

Output Class	arr	48 32.0%	1 0.7%	2 1.3%	94.1% 5.9%
	chf	1 0.7%	48 32.0%	0 0.0%	98.0% 2.0%
	nsr	1 0.7%	1 0.7%	48 32.0%	96.0% 4.0%
		96.0% 4.0%	96.0% 4.0%	96.0% 4.0%	96.0% 4.0%
	arr	chf	nsr		
	Target Class				

Figure 11- Confusion matrix (GoogleNet)

Confusion Matrix

Output Class	arr	46 30.7%	0 0.0%	1 0.7%	97.9% 2.1%
	chf	0 0.0%	46 30.7%	2 1.3%	95.8% 4.2%
	nsr	4 2.7%	4 2.7%	47 31.3%	85.5% 14.5%
		92.0% 8.0%	92.0% 8.0%	94.0% 6.0%	92.7% 7.3%
	arr	chf	nsr		
	Target Class				

Figure 12- Confusion matrix (AlexNet)

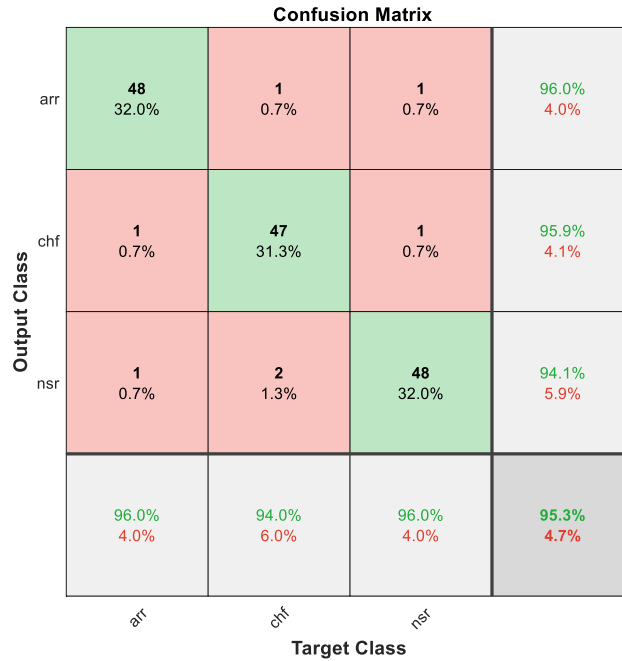


Figure 13- Confusion matrix (ResNet)

Figures 14, 15 and 16 show the classification of eight test image scalograms, using the modified deep-CNN model (transfer learning) for all three of our models. The results show the classification efficiency of these models.

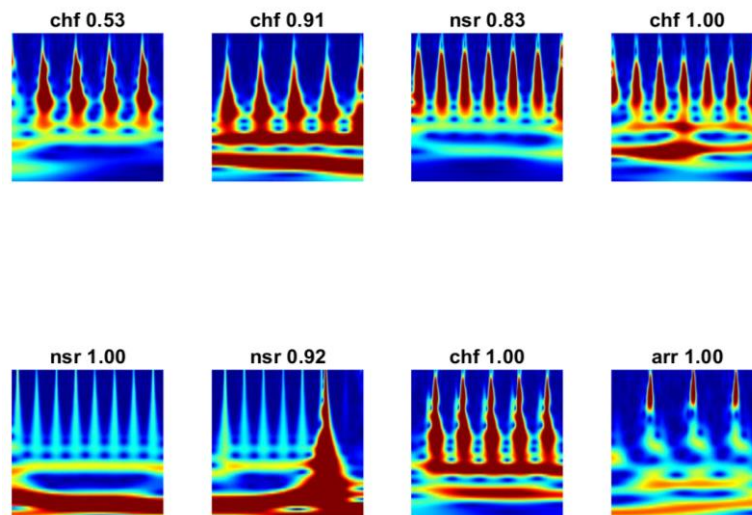


Figure 14- Classifications of eight scalogram images (ECG signal) with the modified deep-CNN model (GoogleNet).

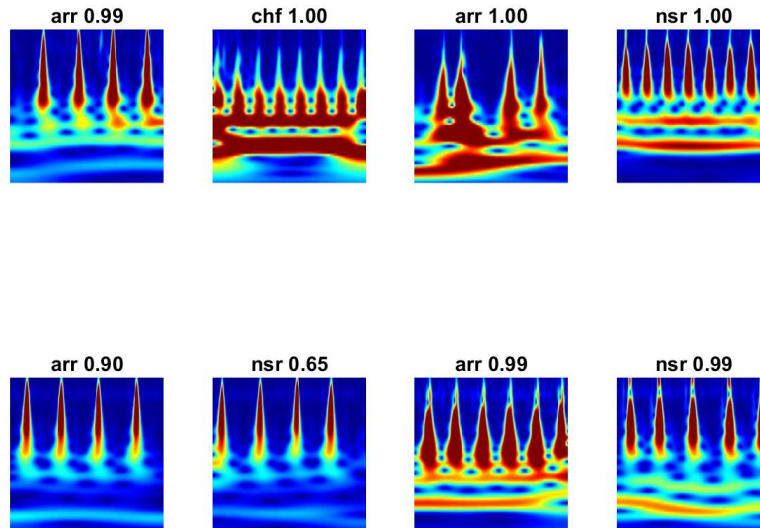


Figure 15- Classifications of eight scalogram images (ECG signal) with the modified deep-CNN model (AlexNet).

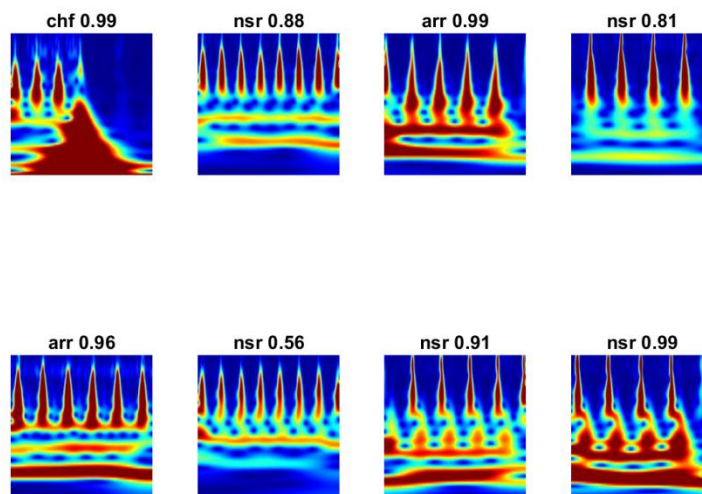


Figure 16- Classifications of eight scalogram images (ECG signal) with the modified deep-CNN model (ResNet).

4.2. Discussions

The three deep CNN models, GoogLeNet, AlexNet and ResNet, performed well in classification of ECG signals. They all achieved high accuracy rates, indicating their ability to correctly classify scalogram images as ARR, CHF or NSR.

Comparing the performance of the three models, GoogLeNet achieved the best overall accuracy, closely followed by ResNet and AlexNet. However, all models showed similar performance in terms of recall, accuracy and F1 score, demonstrating a similar ability to identify positive pneumonia cases.

It is important to note that these results are based on an assessment specific to the dataset used and may vary depending on the quality of the dataset and the training parameters chosen. It is

recommended to perform cross-validation and test models on different datasets to obtain a more robust assessment of their performance.

5. Conclusion

In this study, we have developed a classification model that integrates the continuous wavelet transform (CWT) with a deep learning network to effectively classify ECG signals into three categories: Normal Sinus Rhythm (NSR), Congestive Heart Failure (CHF), and Arrhythmia (ARR). The ECG signals used in this study were obtained from publicly available databases, namely MIT-BIH and BMDMC. To facilitate the classification process, the 900 one-dimensional ECG recordings were transformed into 2D RGB scalograms. These scalogram images were then fed into deep neural networks, specifically the GoogLeNet, AlexNet, and ResNet models. The dataset was split into training and test sets to evaluate the performance of the models. In conclusion, the utilization of machine learning models, such as GoogLeNet, AlexNet, and ResNet, for the classification of ECG signals represents a significant advancement in the field of computer-aided diagnosis. The results of our work have demonstrated that these CNN models achieved high performance in the automatic classification of ECG signals. This indicates that these models are capable of learning to recognize specific characteristics of ECG signals and provide accurate classification.

The experimental results have highlighted the effectiveness of integrating continuous wavelet transform (CWT) with deep neural networks, specifically GoogLeNet, ResNet, and AlexNet, for detecting cardiac abnormalities from ECG signals. These models achieved impressive average accuracies of 96.00%, 95%, and 93% respectively, emphasizing their performance in classification tasks.

Moreover, the use of 2D deep-CNN models, notably GoogLeNet, demonstrated excellent classification accuracies, making them highly suitable for arrhythmia diagnosis and automated classification in diverse medical applications.

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Conflict of Interests: Authors declare no conflict of interests to this work.

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