Adapting Transfer Learning for Accurate ECG-Based Heart Disease Classification

Sania Urooj[*1], Humera Farooq[2], Muhammad Farrukh Shahid[1]
[1]Department of Artificial Intelligence, FAST National University, Karachi, Sindh, Pakistan.
[2]Department of Computer Science, Bahria University, Karachi, Sindh, Pakistan.
[*]**Correspondence:** sania.urooj@nu.edu.pk

Citation | Urooj. S, Farooq. H, Shahid. M. F, "Adapting Transfer Learning for Accurate ECG Based Heart Disease Classification", IJIST, Special Issue. pp 246-257, Oct 2024
Received | Oct 14, 2024 **Revised |** Oct 17, 2024 **Accepted |** Oct 24, 2024 **Published |** Oct 28, 2024.

ECG signals are widely used for analyzing heart rhythms and detecting abnormalities. This study presents an experimental evaluation of a Deep CNN model for classifying ECG scalograms. Using publicly available datasets containing records from 242 patients, the study aims to classify three different cardiovascular diseases: Congestive Heart Failure (CHF), Myocardial Infarction (MI), and Coronary Artery Disease (CAD). The raw ECG signals undergo several preprocessing steps, including up-sampling, removal of noise and artifacts, and conversion into 2D images. Continuous Wavelet Transform (CWT) is applied to represent the ECG signals as 2D scalograms. The experiments in this work are conducted using a Deep CNN model and the pre-trained Inception V3 model, which achieved accuracies of 96.87% and 90.11%, respectively, on the CWT scalograms of the ECG datasets. The results were thoroughly analyzed, and the model's performance was compared with other existing studies in the field.

Keywords: Cardiac Heart Disease, Electrocardiogram, Convolution Neural Network, Transfer Learning.

Introduction:

Cardiovascular Disease (CVD) is a leading cause of mortality worldwide and poses a significant threat to human health. One of the most commonly used methods for detecting abnormal heart rhythms is the analysis of Electrocardiogram (ECG) recordings. ECG signals provide critical information that helps predict abnormalities in the form of waves or rhythms. By analyzing ECG signals, the heart's electrical activity can be examined from different angles and positions, enabling the identification of various heart diseases, including Cardiac Arrhythmia (CA), Cardiomyopathy, Pericardial disease, coronary artery disease (CAD), Congestive Heart Failure (CHF), and Myocardial Infarction (MI).

ECG is a vital diagnostic tool in cardiology, offering valuable morphological data about a patient's heart rhythms. The visual inspection of these morphological changes, along with a manual interpretation of specific characteristics, plays a crucial role in identifying heart rhythm disorders. Early detection of heart disease through automatic computer-aided diagnostic (CAD) systems can significantly reduce mortality rates and improve overall health outcomes. Thus, monitoring and automating the interpretation of real-time ECG signals for heart disease detection is essential for timely and accurate diagnosis.

A significant amount of research has been dedicated to the automatic diagnosis of CVD and the classification of heartbeats [1-3]. Over the years, Deep Learning (DL) techniques have shown remarkable results in both classification and feature extraction tasks. This study specifically focuses on the multi-classification of three major heart diseases—Congestive Heart Failure (CHF), Coronary Artery Disease (CAD), and Myocardial Infarction (MI)—using 2D ECG data. The classification of 2-dimensional ECG data in the context of CVD is relatively underexplored in existing literature. Researchers have primarily focused on feature extraction and classification methods using machine learning algorithms. Notable studies have proposed various techniques for classifying heart diseases, such as CAD [2, 4-20]. For instance, a novel algorithm was introduced for the automated characterization of multiple CVDs, including MI, CHF, CAD, and normal ECG (four classes) [9], while another model focused on detecting four classes of heart diseases (CHF, CAD, MI, and normal) [10], though it suffered from high computational time during feature selection.

As deep learning approaches gained prominence, several groundbreaking contributions have been made to the automatic detection of CVDs [2, 4-8, 11-16, 18, 19]. One such contribution is a robust model that combines deep CNN architecture with LSTM for detecting three cardiac abnormalities (MI, CAD, and CHF), though it requires large datasets for training and testing. Another study used 1D ECG data from Physionet [21] but did not apply preprocessing steps like noise removal or segmentation.

For ECG signal classification, 2D CNN models have also been explored, particularly for arrhythmia classification [12-15]. These models require 2D transformations to convert time-series data into 2D images. The classification of 2-dimensional ECG data remains rare in CVD research. In [12], the author compared 1D and 2D ECG signal classification models, demonstrating that 2D CNNs could classify cardiac arrhythmia with 99.02% accuracy. In another study, a CNN model with Continuous Wavelet Transform (CWT) was developed for automatic ECG classification, converting ECG signals into the time-frequency domain [16]. Additionally, novel transfer learning models have been evaluated for early myocardial infarction detection, such as the retrained VGG-Net architecture, which created two networks, VGG-MI1 and VGG-MI2, to enhance model stability and reduce computational overhead for real-time ECG analysis [19].

To address data imbalance, methods such as transforming time-series data into Gramian Angular Summation Field (GASF) images have been proposed [4], ensuring the model learns effectively from minority samples. Other studies have successfully classified arrhythmic heartbeats using 2D CNNs, comparing them to architectures like ResNet and LeNet, and achieving high accuracy rates (97.3%) [18]. In a study by [22], the MobileNetV2-BiLSTM architecture, combined with a matching pursuit algorithm, achieved 91.7% accuracy in detecting arrhythmias. Similarly, a bimodal CNN model developed in [8] achieved 95.73% accuracy in CVD detection, while the Fuzz-Clust Net, which combines deep learning with fuzzy clustering, achieved an impressive 98.66% accuracy in classifying arrhythmias from the MIT-BIH Arrhythmia Dataset [23].

Despite these advancements, existing research still faces challenges in utilizing multiple databases with complex and heterogeneous ECG data. While studies on arrhythmia datasets using 2D ECG images have been successful, there is limited literature on the multi-class classification of CVDs, including MI, CAD, and CHF, using 2D ECG data. To the best of our knowledge, no existing work addresses the classification of these cardiovascular diseases (MI, CAD, and CHF) using 2D ECG images. This study aims to bridge this gap by developing a deep learning-based approach for the automatic detection of CVD through the multi-class classification of three diseases—CHF, MI, and CAD—along with normal ECG waves.

The rest of this article is organized as follows: Section 2 describes the methodology, including data preprocessing and the proposed method. Section 3 presents the results and discussion, and Section 4 concludes the study.

Novelty Statement:

This study addresses the classification of multiple heart diseases by treating it as a multi-class classification problem within a single unified system. Unlike traditional approaches that rely on 1-D ECG signals, the proposed model is trained and tested using 2-D ECG data, offering a more comprehensive representation of the heart's electrical activity for improved diagnostic accuracy.

Objectives:

- To apply Continuous Wavelet Transform (CWT) for converting 1D ECG signals into 2D ECG scalograms.
- To propose a 2D CNN model for the multi-class classification of cardiovascular diseases (normal, CAD, MI, and CHF) using 2D ECG images.
- To explore the application of transfer learning techniques on the ECG dataset.
- To test and validate the performance of the proposed learning models.

Material and Methods:

The primary objective of this study is to identify patterns in ECG signals associated with four different heart diseases and classify them accordingly. This section provides a detailed explanation of the methodology used to implement the proposed approach, including data pre-processing, deep CNN modeling, and the application of a pre-trained model. A visual representation of the entire process is shown in Figure 1.

The proposed approach for this experimental study involves several key steps: from signal acquisition, through training a model on four distinct datasets, to classifying three cardiovascular diseases (CVDs) and normal subjects. The first step is data acquisition, where ECG data from multiple existing databases is collected. The raw ECG signals must then undergo pre-processing before they can be used for classification. The next critical step is transforming the 1D ECG signals into 2D images using wavelet transform. These 2D ECG images, generated from the wavelet transformation, will then be fed into a deep-learning model for both training and testing.

Dataset Overview:

The ECG signals used in this research were sourced from various publicly available databases in the Physionet repository [21]. As detailed in Table 1, the PTB (Physikalisch-Technische Bundesanstalt) database includes 52 normal and 148 Myocardial Infarction (MI) records, all with a sampling frequency of 1000 Hz. The BIDMC CHF database contains recordings from 11 male and 4 female patients diagnosed with congestive heart failure. Additionally, 17 records from 7 Coronary Artery Disease (CAD) subjects were collected from St. Petersburg, with each record being 30 minutes in duration and sampled at 257 Hz. For this study, only the Lead II ECG signals were used from each of these databases.

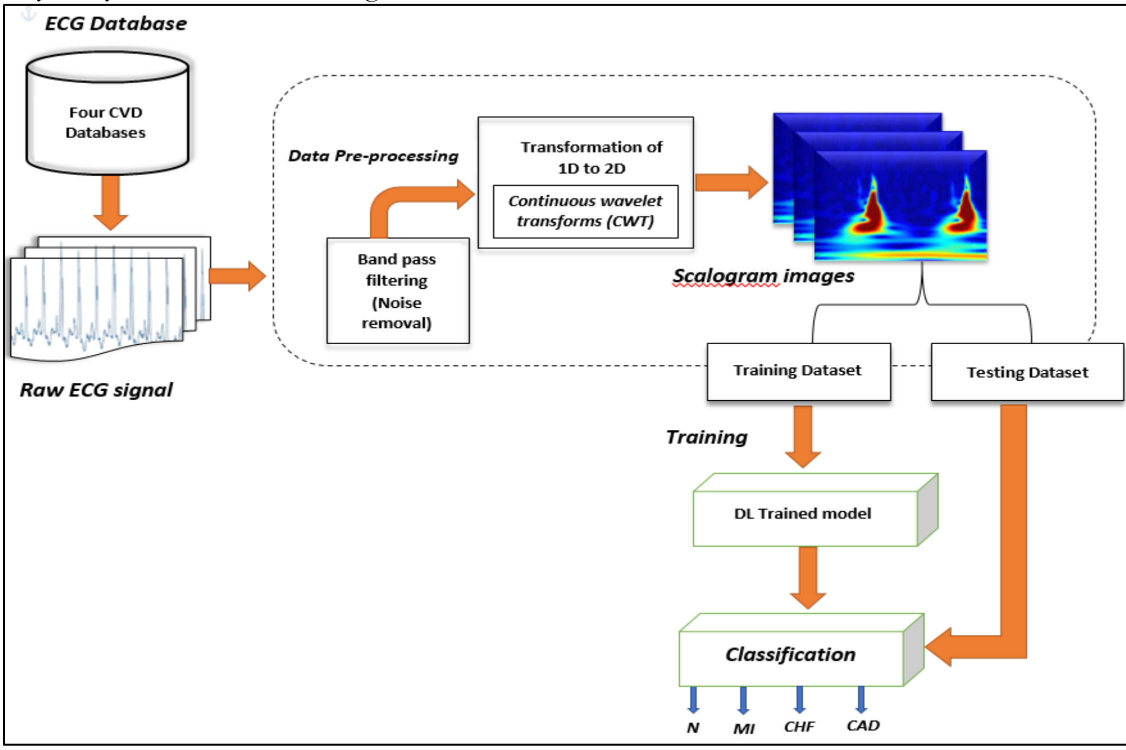

Figure 1. Block diagram of the proposed methodology

Table 1. Summary of Datasets Used

Databases	Diagnosis	No of Subjects	Length Record (hrs.)	Sampling Frequency (Hz)
PTB diagnostic	Normal	52	Varies about 1	1000
Fantasia		20		250
PTB Diagnostic	MI	148	Varies	100
BIDMC	CHF	15	About 2	250
St. Petersburg	CAD	7	0.5	257

Data Pre-Processing:

Different databases used in this study have varying sampling frequencies: the ECG data from the CHF database is sampled at 250 Hz, while the ECG data from normal patients in the PTB diagnostic database is sampled at 1000 Hz. To ensure consistency across the datasets, it is necessary to standardize the sampling frequencies. There are two approaches to achieve this: upsampling or downsampling. As discussed in [9-12], upsampling (i.e., increasing the frequency from 250 Hz to 1000 Hz) is typically preferred, although some studies opt for downsampling depending on their requirements. It is important to note that downsampling may result in the loss of valuable information from the ECG signal. Therefore, in this work, we chose to upsample the two databases (CHF at 250 Hz and CAD at 257 Hz) to match the 1000 Hz frequency of the PTB database.

ECG signals are often corrupted by various types of noise, which can obscure critical health information and lead to misdiagnosis, particularly in telemedicine applications. Common types of noise in ECG signals include power line interference and baseline wander. To mitigate this, we applied a band-pass filter during preprocessing. The low-pass filter (LPF) removes high-frequency components such as power line interference and T-wave noise, while the high-pass filter (HPF) eliminates low-frequency components, such as baseline drift, from the signal.

Continuous Wavelet Transform (CWT):

There are several state-of-the-art methods available for representing signals as images [2, 4, 8, 12-19]. In this research, we adopt a 2D deep neural network for the classification of 2-dimensional ECG data, which requires transforming 1D data into a 2D format. To achieve this, we use the scalogram representation in the time-frequency domain, obtained through Continuous Wavelet Transform (CWT). The ECG signals are decomposed using CWT to extract various time-frequency components. Wavelet transformation is widely utilized in image recognition tasks as it decomposes complex information into simpler, more interpretable forms. CWT offers the advantage of providing high-time resolution and low-frequency resolution, or vice versa, by adjusting the scale and translation parameters. In our study, the signal is transformed using the Amor mother wavelet function.

In line with the approach used in [11], segmentation was performed on the dataset using 2-second (2000-sample) windows. Each ECG recording was divided into data instances of the same length, resulting in multiple scalograms for each record. These scalograms were resized to 224x224 pixels and 128x128 pixels for use with a pre-trained model and a deep 2D CNN, respectively. Figure 2 illustrates the CHF ECG signal along with its corresponding CWT scalogram.

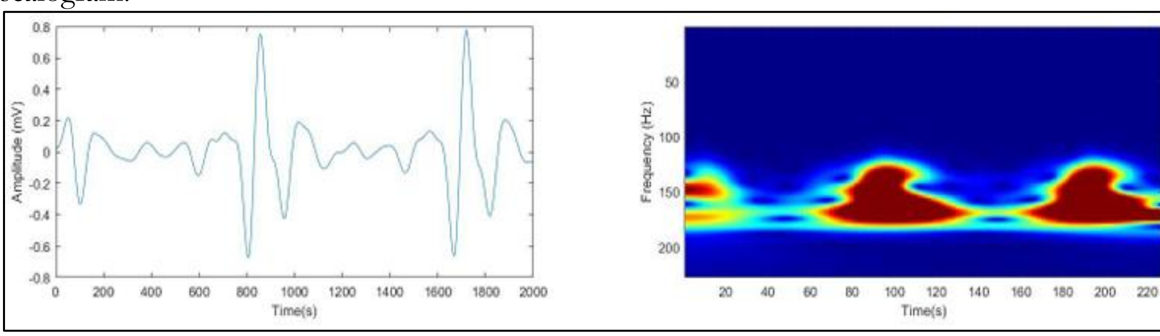

Figure 2. ECG signal with CWT scalogram

After the pre-processing step, a total of 98,870 ECG images were generated. The breakdown of ECG images obtained for each class—CAD, CHF, MI, and normal—is provided in Table 2.

Table 2. Number of ECG Images of Each Class

ECG Type	ECG Scalograms
Normal	4703 (PTB) + 30,000 (Fantasia)
MI	18,867
CHF	30,000
CAD	15,300

Proposed Deep 2D CNN:

After pre-processing the ECG signals, a set of time-frequency scalograms is generated and provided as input to the CNN model for classification. Convolutional Neural Networks (CNNs) are highly effective for image processing and computer vision tasks, making them ideal for this application. A typical CNN architecture consists of three main types of layers: the convolutional layer, the pooling layer, and the fully connected layer. The convolutional layer, combined with the ReLU activation function, and the pooling layer are arranged in a repetitive sequence to extract features from the input data [24].

Each input matrix of an image X is convolved with the kernel and bias is added to each output. Hence, the output F_n is the sum of the bias b and multiplied value of the kernel K with input image X. It can be written in mathematical form as:

$$F_n = \sum_{i=1}^{n} X_i * K + b \qquad (1)$$

In this study, the CNN model used for multi-class classification is inspired by the architecture presented in [25]. The model consists of three convolutional layers, three max-pooling layers, and two fully connected layers. Each convolutional layer has a kernel size of 5x5 and employs 20, 50, and 100 filters, respectively, with a stride of 2. Following each convolutional layer, a max-pooling layer with a 2x2 kernel size and a stride of 2 is applied. A summary of the CNN architecture is provided in Table 3.

InceptionV3:

Deep learning techniques are inspired by the architecture of neural networks, which use hidden layers to simulate neuron input and output processes for learning, thereby improving performance with each iteration [26]. These algorithms have significantly advanced diagnostic systems, particularly in medical imaging [2, 4-8, 11-16, 18, 19, 27]. In this study, we employ a 'fine-tuning' approach to train our model, leveraging transfer learning, which has been shown to deliver optimal performance in medical imaging tasks [5, 8, 19, 28]. The ECG images are fed into a well-established pre-trained model, InceptionV3, developed by Google as part of the Deep Learning Evolutionary Architectures series [27].

The InceptionV3 model consists of three main components: a convolution block, an enhanced Inception module, and a classifier. For our task, the pre-trained model is fine-tuned by modifying its parameters and layers to better suit the classification of ECG images. Since the InceptionV3 model has already been trained on the large ImageNet database, which includes 1,000 classes, extensive retraining is not necessary. Instead, we only fine-tune the final fully connected layer, adjusting it to output four classes: CAD, CHF, MI, and Normal (N). This approach allows the model to leverage its pre-trained knowledge while adapting to the specific needs of our ECG classification task.

Table 3. Summary of the Layers of Proposed CNN Architecture

S. No	Layer Name	Kernel size	Filters	Stride	Output Shape
1	Conv2D	5 x 5	20	1	128, 128, 20
2	Max pooling	5 x 5	-	2	64, 64, 20
3	Conv2D	5 x 5	50	1	64, 64, 50
4	Max pooling	5 x 5	-	2	32, 32, 50
5	Conv2D	5 x 5	100	1	32, 32, 100
6	Max pooling	5 x 5	-	2	16, 16, 100
7	Flatten	-	-	-	25600
8	Dense	-	-	-	500
9	Soft max	-	-	-	4

In this study, ECG images are used to detect abnormal heartbeats associated with four different heart diseases: CAD, CHF, MI, and normal patients. The ECG datasets for these four classes were downloaded from an online source [21] and used for training and testing the classification model. To convert the 1-dimensional ECG data into a 2-dimensional format suitable for deep learning, Continuous Wavelet Transform (CWT) was applied. The classification results were obtained using two distinct deep-learning models.

First, a 2D-CNN model was employed for the classification of ECG scalograms, and its performance was evaluated. In the second experiment, the ECG scalograms were classified using the pre-trained InceptionV3 model, and the results were compared. The experiments were based on multi-class classification of ECG data and were performed on a system equipped with an Intel® Core™ i9-10850K CPU (3.6 GHz), 64 GB of RAM, and an NVIDIA RTX 3060 GPU with 12 GB memory. The operating system used was Windows 10 Pro, with a 64-bit system architecture. The 2D ECG images were split into training and testing datasets, with 80% used for training and 20% reserved for testing.

To enhance the model's performance and ensure generalizability, we applied 5-fold cross-validation during the training process. This approach allowed us to obtain average results from all folds on the test dataset. The model's performance was evaluated using several metrics, including sensitivity, specificity, precision, F1 score, and accuracy. Each image in the dataset was resized to (224, 224, 3), where 224 represents the height and width of the image, and 3 corresponds to the number of color channels in the image (RGB). The layers of the pre-trained InceptionV3 model were frozen, except for the top layer, to prevent updating the weights during training. The learning rate, batch size, and number of epochs were set to 0.001, 16, and 50, respectively. These hyperparameters were carefully chosen to avoid overfitting. The Stochastic Gradient Descent (SGD) optimizer was used for training, and since this is a multi-class classification problem, the 'categorical cross-entropy' loss function was employed.

Result and Discussion:

Experimental studies were conducted on ECG scalograms derived from the ECG signals listed in Table 2. The CNN model was trained using 61,846 samples, with 12,370 samples used for validation. The testing set consisted of 15,458 samples. The confusion matrix for the deep 2D CNN model, which classifies images into the categories of Normal, CAD, CHF, and MI, is presented in Figure 3.

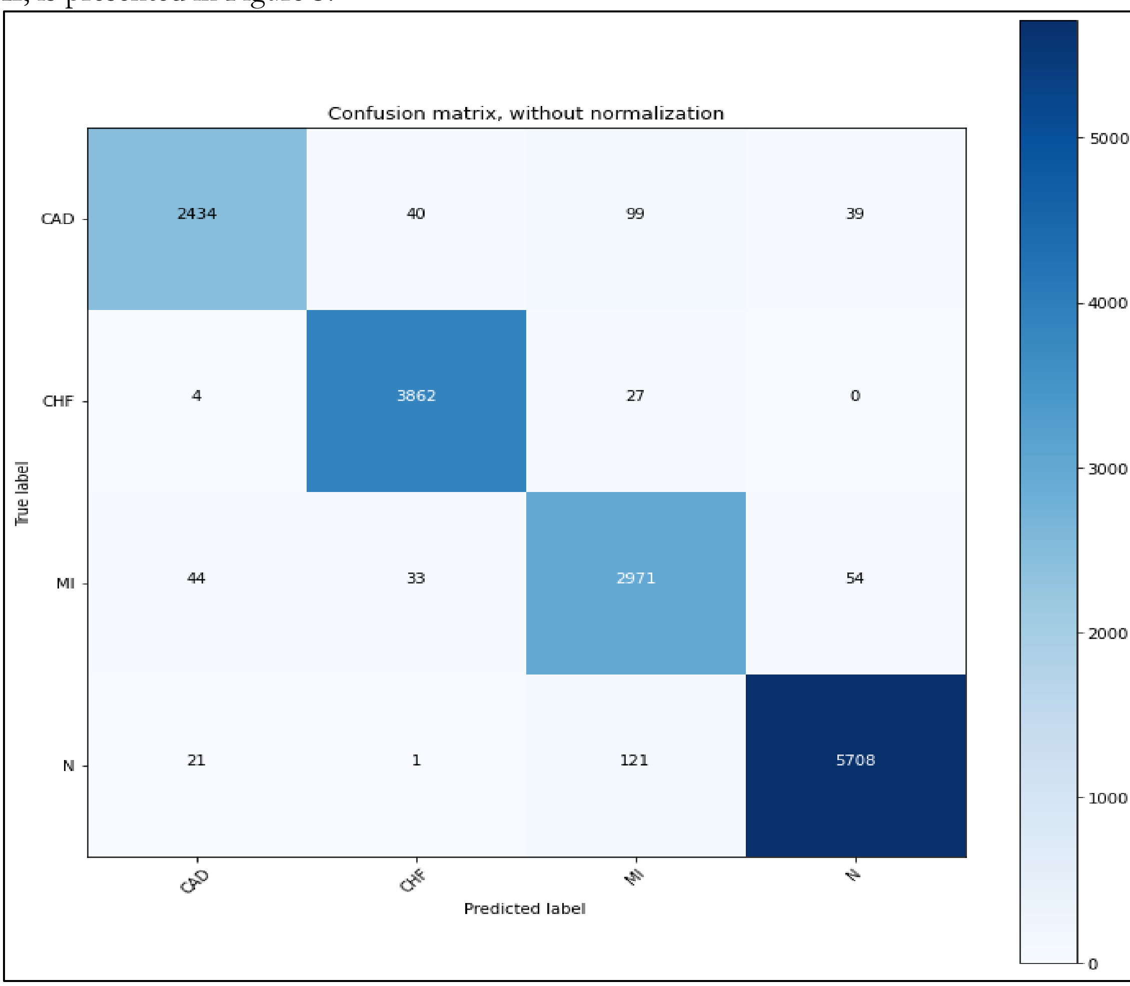

Figure 3. Confusion Matrix of 2D Deep CNN

Table 4 presents a comparison of classification performance across different classes for the deep 2D CNN model. Notably, the model accurately classifies 97.2% of ECG images as CAD, 99.3% as CHF, 92.3% as MI, and 98.3% as Normal. During the training phase, the Deep CNN model effectively processed ECG scalograms without causing overfitting. The model achieved a validation accuracy of 98%, while the training accuracy reached 100%.

Table 4. Performance Values of 2D CNN Model on ECG Test Data.

Classes	Accuracy %	Precision %	Sensitivity %	Specificity %	F1-Score %	Overall Accuracy %
CAD	98.3	97.2	93.1	99.4	94.9	96.87
CHF	99.3	98.1	99.2	99.3	98.6	
MI	97.5	92.3	95.77	97.9	93.9	
Normal	98.4	98.3	97.5	99.0	98.0	

In the second phase of this study, the transfer learning model, InceptionV3, was trained for the multi-class classification of cardiovascular diseases (CVDs), including normal, CAD, MI, and CHF, using 2D ECG images. The confusion matrix for InceptionV3's classification of Normal, CAD, CHF, and MI images is shown in Figure 4. The average accuracy of the model is calculated by averaging the diagonal values of the matrix, yielding an overall accuracy of 90.1%. Table 5 provides a detailed performance evaluation of heart disease classification using InceptionV3, presenting accuracy, precision, sensitivity, specificity, and F1-score for all classes.

Table 6 compares the performance of the InceptionV3 model with a conventional convolutional neural network (CNN) model. It is observed that earlier studies focused on different feature engineering techniques combined with machine learning algorithms [9, 10]. For instance, [10] employed contourlet and shearlet transformations for feature extraction, using KNN and decision tree classifiers to classify ECG signals, achieving an accuracy of 99.5%. Similarly, [11] classified multiple cardiovascular diseases using 1D ECG data, incorporating deep CNN along with LSTM for better performance. While these studies reported good results for multi-class classification of CAD, CHF, MI, and normal signals, they were limited to 1D ECG data. In contrast, our proposed model utilizes 2D ECG data, where the ECG signals are decomposed by CWT to generate various time-frequency components, which are then classified using a CNN model.

Table 7 provides a summary of classification performance based on ECG images. Several studies in the literature have focused on the classification of multiple arrhythmia classes [14, 15, 17, 18], using 2D representations of signals through methods such as continuous wavelet transform (CWT) and short-time Fourier transform (STFT). However, to our knowledge, no study has specifically transformed CAD, CHF, MI, and normal signals into time-frequency domain scalograms and performed classification on these. Our comparison with existing models highlights a key distinction: our approach focuses on detecting various heart diseases, not just classifying ECG beats from similar diseases. While studies have achieved high accuracy (99%) in classifying seven classes of arrhythmia using 2D ECG signals derived from CWT [12, 13], these studies often require significant training time due to large kernel sizes. In contrast, our study produced two results using two different models. The deep 2D CNN model achieved 96.87% accuracy and a negligible overall average loss of 0.01%.

Furthermore, Table 8 notes that previous studies have utilized models such as Alex Net, VGGNet, and DenseNet for ECG image classification. In this study, InceptionV3 was employed in the second phase, yielding a testing accuracy of 90.11% when four datasets containing ECG scalograms were used for training. The variation in performance compared to existing studies can be attributed to differences in disease types, the number of classes, and the test size. However, the novelty of this work lies in the application of a pre-trained InceptionV3 model to classify multiple heart diseases using 2D ECG data. The main advantage of this study is its ability to classify various heart diseases within a single unified system. Moreover, the transfer of learned features from the pre-trained model to the target task is a significant benefit. Nonetheless, the study highlights that a large volume of high-quality, well-labeled training data is crucial for achieving even better performance. Expanding the dataset with additional, diverse samples would likely further improve the model's accuracy and generalizability.

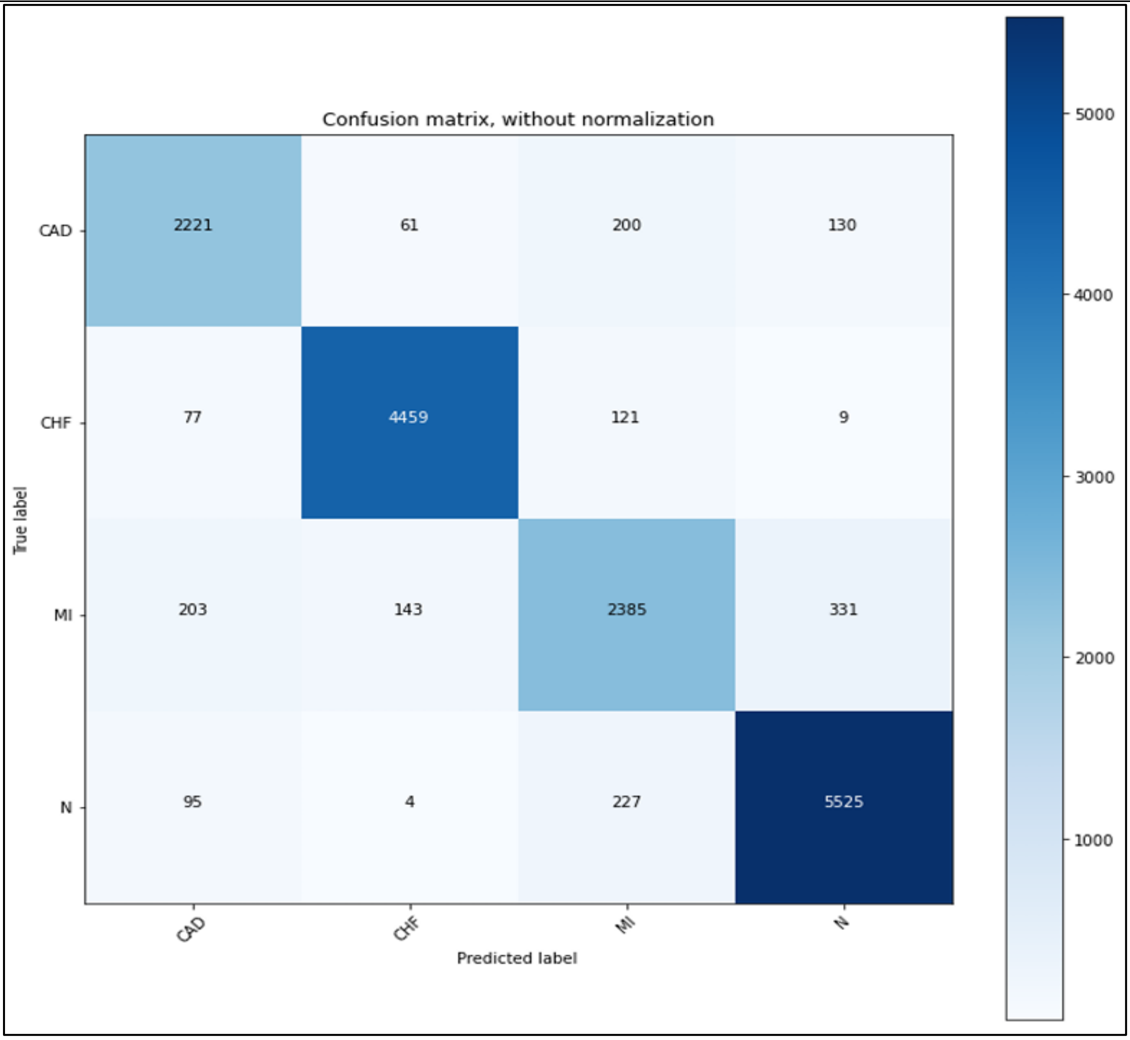

Figure 4. Confusion Matrix of InceptionV3

Table 5. Performance values of InceptionV3 on ECG test data.

Classes	Accuracy %	Precision %	Sensitivity %	Specificity %	F1-Score %	Overall Accuracy %
CAD	95.0	85.5	85.0	97.0	90.8	90.11
CHF	96.0	96.6	95.5	98.0	96.0	
MI	92.2	81.31	77.89	95.7	79.5	
Normal	93.2	92.1	94.4	95.0	93.2	

Table 6. Comparison of the Proposed Model with State-Of-The Art Studies on Multi-Classification for Cardiovascular Disease

Authors	No. of Classes	Classifier	Accuracy
[9]	Four datasets normal, CAD, CAD, and MI	KNN and DT classifiers	97.98%
[10]		K-Nearest Neighbour (KNN)	99.55%
[11]		Deep CNN + LSTM	98.50%
Proposed Approach		Deep CNN	96.87%

Table 7. Comparison of the Proposed Model with State-Of-The Art Studies on ECG Images Classification Using 2D CNN

Authors	Disease	No. of Classes	Accuracy
[12]		Seven classes of arrhythmia	99.02%

[13]	Arrhythmia	Seven classes of arrhythmia	99.11%
[14]		Five different classes of arrhythmia	99.01%
[16]		4 classes of arrhythmia	98.74%
[18]		4 classes of arrhythmia	99.74
[17]		5 classes of arrhythmia	98.87%
[20]	Cardio vascular diseases	2 classes of CVD's (ARR, CHF)	97.3%
Proposed Approach		3 classes of CVD's (CAD, CHF, MI)	96.87%

Table 8. Comparison of the proposed model with state-of-the art Transfer learning techniques

Authors	Disease	No. of Classes	Classifier with Accuracy
[19]	Myocardial Infarction	Two classes: Normal and abnormal	VGG net model =99.40%
[18]	Arrhythmia	4 classes: Normal, PB, LBBB, RBBB and PVC	Resnet50= 98.2%, LeNet=97.4%
[13]		Seven classes: VFW, PVC, VEB, RBB, LBB, PAB, and APC	Alex Net =98.85%, VGG net= 98.90%
[4]		5 classes RBBB, LBBB, APC, PVC and Normal	CBAM Res Net: 98.29%
[8]		4 classes AFIB, GSVT, SB, and SR	InceptionV3=95.73%
[5]	Cardio vascular diseases	2 classes of CVD's (CHF, ARR)	Alex Net =98.74%
Our Proposed approach	Cardio vascular diseases	4 classes of CVD's	(CAD, CHF, MI, Normal) InceptionV3= 90.110%

By comparing the proposed model with existing studies that employ different models, it is evident that our system achieves superior classification performance using 2D ECG data. Additionally, our approach successfully classifies multiple heart diseases within a single model, showcasing its versatility. While the proposed model offers several advantages, it also has certain limitations, which are outlined below:

A large volume of data is essential for improving the model's performance. Expanding the dataset could significantly enhance the system's accuracy and robustness. This study utilized data from only 7 CAD patients, which may limit the model's generalizability. Increasing the number of samples, particularly for CAD, would likely lead to better performance. Training the model requires substantial computational resources, including powerful hardware and extended processing times, which could be a barrier to real-time deployment in resource-constrained environments.

Conclusion:

Accurate classification of irregular ECG signals plays a crucial role in the diagnosis of cardiovascular diseases, offering significant benefits in early detection and reducing the risk of developing these conditions. Convolutional neural networks (CNNs) have proven to be highly effective in enhancing the accuracy of medical imaging systems. This paper presents both theoretical and experimental studies on a two-dimensional ECG classifier for detecting three major cardiovascular diseases. We propose a deep-learning approach using ECG scalograms for classifying four distinct types of heart signals. A large dataset comprising 98,870 images from 242 subjects was utilized for this purpose.

Two models, namely a 2D deep CNN and InceptionV3, were trained and evaluated using ECG images, rather than the traditional 1D ECG signals. Continuous wavelet transforms (CWT) were employed to generate these ECG scalograms, which were then fed into the models for training and testing. The first model, 2D CNN, achieved an impressive accuracy of 96.87% with a precision of 96.91%. To further validate the model's robustness, five-fold cross-validation was applied.

Our current research lays the groundwork for future advancements in ECG classification. Moving forward, we aim to improve the CNN model's performance by fine-tuning its hyperparameters. Additionally, future work will explore the potential of using pre-trained models, such as InceptionV3, and emerging techniques like vision transformers for classifying heart diseases.

Acknowledgment: The authors would like to thank Bahria University for facilitating access to their high-performance computing lab.

Author's Contribution: Sania Urooj: Conceptualization, development, Writing. Humera Farooq: Supervision and Writing, Muhammad Farrukh Shahid: Writing and Proof Reading.

Conflict of Interest: There is no conflict of interest.

Project Details. Nil

References:

1. Denysyuk, H.V., et al., Algorithms for automated diagnosis of cardiovascular diseases based on ECG data: A comprehensive systematic review. Heliyon, 2023.
2. Wang, Z., S. Stavrakis, and B. Yao, Hierarchical deep learning with Generative Adversarial Network for automatic cardiac diagnosis from ECG signals. Computers in Biology and Medicine, 2023. **155**: p. 106641.
3. Islam, M.R. and M. Nahiduzzaman, Complex features extraction with deep learning model for the detection of COVID19 from CT scan images using ensemble based machine learning approach. Expert Systems with Applications, 2022. **195**: p. 116554.
4. Ma, K., A.Z. Chang'an, and F. Yang, Multi-classification of arrhythmias using ResNet with CBAM on CWGAN-GP augmented ECG Gramian Angular Summation Field. Biomedical Signal Processing and Control, 2022. **77**: p. 103684.
5. Lu, X., et al., An end-to-end model for ECG signals classification based on residual attention network. Biomedical Signal Processing and Control, 2023. **80**: p. 104369.
6. Rath, A., et al., Improved heart disease detection from ECG signal using deep learning based ensemble model. Sustainable Computing: Informatics and Systems, 2022. **35**: p. 100732.
7. Rath, A., D. Mishra, and G. Panda, Imbalanced ECG signal-based heart disease classification using ensemble machine learning technique. Frontiers in Big Data, 2022. **5**: p. 1021518.
8. Yoon, T. and D. Kang, Bimodal CNN for cardiovascular disease classification by co-training ECG grayscale images and scalograms. Scientific Reports, 2023. **13**(1): p. 2937.
9. Fujita, H., et al., Characterization of cardiovascular diseases using wavelet packet decomposition and nonlinear measures of electrocardiogram signal, in Advances in Artificial Intelligence: From Theory to Practice: 30th International Conference on Industrial Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE 2017, Arras, France, June 27-30, 2017, Proceedings, Part I 30. 2017. p. 259-266.
10. Acharya, U.R., et al., Automated characterization of coronary artery disease, myocardial infarction, and congestive heart failure using contourlet and shearlet transforms of electrocardiogram signal. Knowledge-Based Systems, 2017. **132**: p. 156-166.

11. Lih, O.S., et al., Comprehensive electrocardiographic diagnosis based on deep learning. Artificial intelligence in medicine, 2020. **103**: p. 101789.
12. Ullah, A., et al., A hybrid deep CNN model for abnormal arrhythmia detection based on cardiac ECG signal. Sensors, 2021. **21**(3): p. 951.
13. Ullah, A., et al., Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation. Remote Sensing, 2020. **12**(10): p. 1685.
14. Huang, J., et al., ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network. IEEE access, 2019. **7**: p. 92871-92880.
15. Wasimuddin, M., et al., ECG signal analysis using 2-D image classification with convolutional neural network, in 2019 International Conference on Computational Science and Computational Intelligence (CSCI). 2019. p. 949-954.
16. Wang, T., et al., Automatic ECG classification using continuous wavelet transform and convolutional neural network. Entropy, 2021. **23**(1): p. 119.
17. Mohonta, S.C., M.A. Motin, and D.K. Kumar, Electrocardiogram based arrhythmia classification using wavelet transform with deep learning model. Sensing and Bio-Sensing Research, 2022. **37**: p. 100502.
18. Degirmenci, M., et al., Arrhythmic heartbeat classification using 2d convolutional neural networks. Irbm, 2022. **43**(5): p. 422-433.
19. Alghamdi, A., et al., Detection of myocardial infarction based on novel deep transfer learning methods for urban healthcare in smart cities. Multimedia tools and applications, 2020: p. 1-22.
20. Eltrass, A.S., M.B. Tayel, and A.I. Ammar, Automated ECG multi-class classification system based on combining deep learning features with HRV and ECG measures. Neural Computing and Applications, 2022. **34**(11): p. 8755-8775.
21. Physionet [cited 2020 10 June]; Available from: https://physionet.org/.
22. Shin, S., et al., Lightweight Ensemble Network for Detecting Heart Disease Using ECG Signals. Applied Sciences, 2022. **12**(7): p. 3291.
23. Kumar, S., et al., Fuzz-ClustNet: Coupled fuzzy clustering and deep neural networks for Arrhythmia detection from ECG signals. Computers in Biology and Medicine, 2023: p. 106511.
24. Roberts, D.A., S. Yaida, and B. Hanin, The principles of deep learning theory. 2022: Cambridge University Press Cambridge, MA, USA.
25. Ozdemir, M.A., et al., Abnormal ecg beat detection based on convolutional neural networks, in 2020 medical technologies congress (TIPTEKNO). 2020. p. 1-4.
26. Yao, Q., et al., Multi-class arrhythmia detection from 12-lead varied-length ECG using attention-based time-incremental convolutional neural network. Information Fusion, 2020. **53**: p. 174-182.
27. Mujahid, M., et al., Pneumonia Classification from X-ray Images with Inception-V3 and Convolutional Neural Network. Diagnostics, 2022. **12**(5): p. 1280.
28. Lui, H.W. and K.L. Chow, Multiclass classification of myocardial infarction with convolutional and recurrent neural networks for portable ECG devices. Informatics in Medicine Unlocked, 2018. **13**: p. 26-33.