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Research article

Enhancing heart disease diagnosis through ECG image vectorization-based classification

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ABSTRACT

Heart disease is a major issue, and the severity of its effects can be reduced through early detection and prevention. ECG is an effective diagnostic tool. Automating ECG analysis increases the possibility of timely analysis and prediction of heart conditions, improving patient outcomes. The extraction of heart-related features further enhances the accuracy of ECG-based classification models, paving the way for more effective and efficient online detection and prevention of heart diseases.

The image-vectorization technique suggested in this study produces a vector representation that precisely captures the distinctive features of the heart signal. It involves image cropping, erasing the ECG grid lines, and assigning pixels to distinguish the heart signal from the background. Compared to the feature vector produced by VGG16, the extracted feature vector is 589 times shorter than the feature vector produced by VGG16, which significantly decreased the amount of memory required, increased algorithm convergence, and required less computing power. The feature vector extracted using image-vectorization is used to create the training dataset, which is used to train artificial neural networks (ANNs). The results demonstrate that using image-vectorization techniques improved the performance of machine learning algorithms compared to using conventional feature extraction algorithms like CNNs and VGG16.

1. Introduction

Automated heart disease diagnosis has the potential to provide early warnings of heart problems, enabling timely interventions and support in the early stages of the disease [1]. Early detection of heart problems can facilitate prompt and effective treatment, leading to improved patient outcomes [2]. An electrocardiogram (ECG) report is a type of medical record that details the electrical activity of the heart. Analyzing the ECG image can reveal many heart conditions, such as irregular heart rhythms, coronary artery disease (CAD), heart failure, myocardial infarction (MI), abnormal heartbeat (Abn-HB), history of myocardial infarction (His-MI), and structural heart diseases, as well as confirm the presence of a healthy heart [3].

The capabilities of artificial intelligence (AI) and machine learning (ML) algorithms to identify patterns and subtle changes in data are well-established. Hence, powerful diagnostic models can be created through training and testing ML algorithms on labeled ECG datasets. The developed models can then be used, online, for ECG signal analysis and abnormal cardiac health detection.

Recently, many smartwatches and wearable devices have started to include ECG monitoring features [4,5]. Feeding the recorded

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ECG signal from wearable devices into heart disease diagnostic models (created by ML) can revolutionize heart disease diagnosis and management.

In the literature, numerous studies in heart disease prediction employ a variety of ML algorithms, ECG pre-processing methods, and feature extraction techniques. Key ML approaches include convolutional neural networks (CNNs), Echo state networks, decision trees (DT), random forests (RF), support vector machines (SVM), and long short-term memory networks (LSTM), among others. Pre-processing techniques range from wavelet transforms (WTs) to signal filtering and normalization. Features extracted include P-waves, QRS complexes, T-waves, and various statistical measures. These studies utilize diverse datasets such as MIT-BIH arrhythmia, Cleveland heart disease, and the UCI ML repository, showcasing the broad scope of ECG-based research in heart disease prediction.

The ECG image-vectorization approach, proposed in this paper, focuses on capturing features from the ECG signal and eliminating irrelevant features from the background. By reducing the noise and irrelevant features, the ML algorithms can be trained more effectively, leading to improved accuracy in heart disease classification. In the subsequent section, we explain the problem statement.

1.1. Problem statement

The effectiveness of a machine-learning model is directly influenced by the quality of the extracted features. This study aims to extract discriminating features that capture various heart conditions from ECG images. Many works in the literature use CNNs and other feature extraction tools such as VGG16, ResNet, DenseNet, and Inception to extract features from ECG and then train ML algorithms. Compared to the background, the heart signal is poorly represented in the image, making it challenging to extract heart signal features from the ECG image. For instance, the dimension of a normal ECG image is 2213 pixels in width and 1572 pixels in height, the total number of pixels is $2213 \times 1572 = 3478836$ pixels. With this number of pixels, 63845 represents the heart signal, while 3414991 pixels represent the background. This difference in the number of pixels makes the percentage of the heart signal presence on the image equal 1.83 %, and the percentage of the background presence on the ECG image equals 98.16 %. This can pose a challenge to feature extraction tools when extracting features from the ECG image, as the features are biased toward the background pixels and do not capture important information about the heart signal. Furthermore, any image preprocessing may additionally deteriorate the percentage of heart signal presence on the ECG image, which can exacerbate the class imbalance and make it even more challenging to extract useful features from the ECG image. In particular, this study addresses the following research questions. How to extract distinguishing features of various heart conditions from ECG images, given the substantial class imbalance caused by the biased representation of background pixels and the limited presence of the heart signal pixels? Are off-the-shelf feature extraction tools, such as CNNs and VGG16, capable of effectively identifying distinctive features of different heart diseases in ECG images? What is the impact of image preprocessing on the quality of the extracted features?

The remainder of this work is organized as follows: Section 2 reviews related works in the literature and contrasts their conclusions with the findings of this work. Section 3 explains the background knowledge needed to comprehend the context of this work. The methodology used in this study is thoroughly explained in Section 4. Section 5 offers a thorough analysis of the results and an explanation of the research's conclusions. Section 6 reweighs the conclusions of this work to those presented in the literature review. Finally, Section 7 provides concluding remarks.

2. Literature review

Several approaches have been suggested in the scientific literature to predict heart diseases by applying ML and diverse data preprocessing methods to ECG images. While some experts argue that data preprocessing techniques are crucial to achieving accurate predictions of heart conditions from ECG images, others contend that ML algorithms can be effectively employed without any pre-processing. Additionally, some researchers suggest that the combination of both data preprocessing and ML could yield the most precise predictions possible. The majority of the studies selected for the literature review predominantly utilize ECG imagery in conjunction with ML algorithms for the classification of cardiac diseases.

The work in Ref. [6] proposes a hybrid CNN-Naive Bayes classifier for classifying normal sinus rhythm, abnormal arrhythmia, and congestive heart failure from the MIT-BIH arrhythmia database. The paper uses continuous wavelet transform (CWT) to convert one-dimensional ECG signals to two-dimensional scalogram images. ResNet is used to extract independent and discriminating features that aid the Naive Bayes (NB) classifier in achieving high accuracy in classifying different types of heart diseases. Using the MIT-BIH Arrhythmia dataset, the study in Ref. [7] performed ECG signal classification using multilayer perception (MLP) and support vector machine (SVM) classification techniques to classify the P, Q, R, S, and T waves in ECG signals. Additionally, wave transformation techniques such as discrete wavelet transform (DWT), discrete cosine transform (DCT), and continuous wavelet transform (CWT) were used to increase the success of the classification. The authors of [8] aim to find any cardiac arrhythmias that may be present in the ECG signal. The ECG dataset is pre-processed using DWT to extract features from the QRS complex. The extracted features are fed to the genetic algorithm (GA) and neural networks (NNs) to classify heartbeats. The authors claim that the NN algorithms achieved a higher accuracy and precision rate than GA. Using MIT-BIH arrhythmia data, the study in Ref. [9] proposes a two-dimensional CNNs model to classify ECG signals into eight classes. The methodology transforms the one-dimensional ECG time series signals into 2-D spectrograms through a short-time Fourier transform and uses a 2-D CNNs model to extract robust features. The authors claim to achieve very high classification accuracy. Using data collected from different hospitals, the work in Ref. [10] applies a signal-processing approach to predict CAD using ECG signals. The following numerical features were extracted from ECG: skewness, kurtosis, shape factor, impulse factor, marginal factor, energy, root sum square, spectral entropy, energy entropy, quantile, and Higuchi fractal dimension. The authors asserted that the listed features are informative and achieve better performance. The work in Ref. [11] applied the LSTM algorithm for ECG arrhythmia classification in the UCR time series dataset archive. The preprocessing was done in two steps: first, the heartbeat was extracted, and then the signal was normalized. The work in Ref. [12] uses wavelet transforms (WT) and AlexNet CNNs to classify ECG signals into three categories: arrhythmia, congestive heart failure, and normal sinus rhythm. They collected ECG recordings from the MIT-BIH Arrhythmia Database, the MIT-BIH Normal Sinus Rhythm Database [13], and the BIDMC Congestive Heart Failure Database [14]. The authors asserted that AlexNet achieved better performance. The work in Ref. [15] explores the use of deep learning methods, including edge detection and graph neural networks, for diagnosing cardiovascular diseases through ECG analysis. The authors in Ref. [16] propose a hybrid feature extraction method that combines correlation and regression methods with temporal, morphological, and statistical features to classify ECG signals. The proposed method is evaluated on a back propagation neural network (BPNN) model and traditional ML algorithms, including k-nearest neighbors (KNN), decision tree (DT), and random forest (RF). The study claims that the hybrid feature extraction method positively affected the performance of the classification algorithms. Using ECG data, the authors of [17] propose a model that combines handcrafted and automatic CNNs features for efficient classification. The hybrid feature vector is fed sequentially to a deep learning classifier (LSTM) to predict heart diseases. Using the MIT-BIH databases, the work in Ref. [18] tries to predict sudden cardiac arrest (SCA) using ECG and heart rate variability (HRV) signals. The aim is to investigate the ECG morphological feature, R peak to R–Tend, to predict the imminent SCA 5 min before ventricular fibrillation (VF) onset. Four nonlinear features: the most significant exponent, the Hurst exponent, sample entropy, and approximate entropy, were extracted from the R–Tend beats to train three ML algorithms: SVM, subtractive fuzzy clustering, and neuro-fuzzy classifier. The authors claim that the sample entropy features efficiently predict the SCA 5 min before VF onset using the SVM classifier. Using the dataset obtained from the Cleveland Clinic, the work in Ref. [19] applies SVM to predict heart disease risk levels. The dataset consisted of 303 records with 13 attributes. A boosting technique was used to select relevant features. The results showed that SVM performed better than linear regression (LR), NB, DT, MLP, and RF. Using the MIT-BIH database, the author [20] tried to classify heart diseases using SVM. The ECG signals are filtered to remove noise and segmented into smaller pieces. The following features are extracted: R-R interval, QRS peak, mean, variance, skewness, wavelet coefficients, energy, and entropy. The features are then used to train and test the SVM model. Utilizing the UCI ML repository, the authors of [21] study the impact of various feature selection techniques on heart disease classification. The study applied five feature selection techniques. The selected features are then used to train six supervised ML classifiers. The authors asserted that feature selection techniques improved classification performance. The study in Ref. [22] proposes a classifier based on echo state networks. The proposed classifier has low-demanding feature processing, requiring only a single ECG lead. The proposed method has been evaluated in two internationally recognized ECG databases: the MIT-BIH arrhythmia (MIT-BIH AR) and the AHA. The authors of [23] propose a 2-D CNNs approach to classify five different arrhythmia types. The proposed architecture was trained on ECG signals from the MIT-BIH arrhythmia benchmark database. The authors asserted that CNNs achieve high accuracy during testing without preprocessing or feature extraction/selection stages. The goal of [24] is to classify ECG signals into five rhythms: regular beat, supraventricular ectopic beat, ventricular ectopic beat, fusion beat, and unknown beat. The authors apply CNNs to the dataset publicly available from MIT-BIH ECG. The authors do not mention a specific preprocessing technique. Using ECG images from MIT-BIH, the authors in Ref. [25] pre-processed ECG images to extract the following features: P-wave, QRS complex, and T-wave signals. These features are then fed into the CNNs algorithm for classification. The work claims high accuracy in abnormality detection. The work in Ref. [26] focuses on arrhythmia classification using a 2D-CNNs model optimized for edge devices. The study in Ref. [27] proposes using elemental symptoms and health factors as input features to the KNN and DT algorithms. The dataset consists of 1025 instances and 14 features. The study reports that KNN achieved 85 % accuracy and DT achieved above 90 % accuracy for predicting the vulnerability of heart disease. The authors of [28] apply CNNs, deep belief networks (DBN), recurrent neural networks (RNN), LSTM, and gated recurrent units (GRU) to classify heart disease conditions based on ECG signals. CNNs are the most commonly used technique for feature extraction, and high accuracy was achieved in classifying atrial fibrillation (AF), supraventricular ectopic beats (SVEB), and ventricular ectopic beats (VEB). Using the UCI ML repository, the authors of [29] apply SVM, quadratic SVM, cubic SVM, medium Gaussian SVM, DT, and ensemble subspace discriminant (ESD) for heart disease classification. The study concluded that the quadratic SVM achieved the highest accuracy. The authors in Ref. [30] utilize the Cleveland heart disease datasets to detect and classify coronary heart disease. The dataset initially had 76 attributes for patients, but during the pre-processing step, only 14 were used. The paper used six ML algorithms: NB, MLP, K-Star, LR, DT, and J48. The simulation results demonstrate that the NB algorithm shows better accuracy for predicting coronary diseases. Using ECG image reports, the study in Ref. [31] applied NB, SVM, and XGBoost to detect heart diseases. The author claims that XGBoost algorithm-based heart disease detection achieved higher performance. The study in Ref. [32] presents a three-layer deep genetic ensemble of classifiers (DGEC) for detecting arrhythmia in ECG signals. The model was trained on 744 segments of ECG signals obtained from the MIT-BIH Arrhythmia Database. The results showed that the DGEC system achieved high accuracy, sensitivity, and specificity in detecting 17 arrhythmia ECG classes. Using ECG signals, the authors of [33] classify cardiac conditions using SVM and CNNs. The models were trained and tested on 1000 fragments of ECG signals from 45 patients in the MIT-BIH Arrhythmia Database. The authors asserted that the CNN-based approach achieved higher classification accuracy than SVM. Using the UCI dataset, the authors of [34] train and test RF, SVM, NB, and DT to predict heart disease. The authors found that RF provided the most accurate results in less time than other techniques [35]. analyzes four ML models for heart disease detection and finds that the XGBoost algorithm-based model had the highest accuracy, precision, recall, and F1-measure parameters. The NB with a weighted approach had lower accuracy than the others, and the SVM with duality optimization had lower precision, recall, and F1-measure values. The authors of [36] train 1-D CNNs with the 48 features extracted from MIT/BIH arrhythmia to classify heart disease. They apply WT and principal component analysis (PCA) to denoise the data. The authors claim that CNNs are very useful in dealing with local features. The study in Ref. [37] used the MIT-BIH database with CNNs to identify and screen patients for cardiovascular arrhythmias. The study found that using the exponential linear unit (ELU) activation function achieved better accuracy. The study in Ref. [38] uses a combination of two public datasets: the MIT-BIH Arrhythmia and MIT-BIH

Atrial Fibrillation databases. The study tried two approaches: directly passing the ECG images to CNNs or preprocessing the data first and passing it to CNNs. The authors asserted that the classification accuracy increased after applying preprocessing to the ECG report image compared with inputting the ECG directly without preprocessing. The authors in Ref. [39] analyze the usage of deep learning methods for ECG signal processing. They evaluate commonly used techniques on a dataset of 100,022 beats in five classes and provide insights into the state-of-the-art classification of ECG signals using deep learning. The authors in Ref. [40] overview ML algorithms techniques in analyzing ECG data for the detection and prevention of coronary heart disease. This study aims to address the crucial task of extracting meaningful features from ECG images for heart disease classification problems. Motivated by the demand to extract discriminative features while maintaining low computational resource requirements—a necessity for online heart disease applications—the work presented here focuses on overcoming challenges posed by traditional feature extraction techniques like CNNs, SVM, NB, and XGBoost. Typical ECG images contain only a minor portion of the heart signal, which makes distinguishing essential heart signal features from the background a challenge using traditional feature extraction techniques. To tackle this issue, this paper proposes an image-vectorization approach that is capable of accurately capturing diverse heart condition characteristics from ECG images, even with significant class imbalances resulting from the uneven distribution of background pixels and scarce occurrence of heart signal pixels. Compared to existing literature reviews, the proposed image-vectorization technique presents several benefits, including addressing feature imbalance challenges and facilitating real-time analysis and predictions. Image-vectorized features excel at heart disease classification due to their ability to uniquely identify diverse patterns of heart disease conditions.

3. Preliminaries

The methods and tools used in this study are described in more detail in this section.

3.1. Electrocardiogram (ECG)

An ECG report is a medical record that details the heart's electrical activity, as shown in Fig. 1, details can be found in Ref. [41]. The heart signal is displayed on a grid of lines used as a reference to diagnose various aspects of cardiac health, including an abnormal heartbeat (Abn-HB), myocardial infarction (MI) (heart attack), a history of myocardial infarction (His-MI), and many other heart diseases.

As shown in Fig. 1(A), the ECG image has 4 horizontal lines: *P-wave* (represents the electrical activity of the atria), QRS complex (represents the electrical activity of ventricles), *T-wave* (represents the electrical activity of the ventricles as they relax), and *U-wave* (small waves sometimes follow the *T-wave*). Fig. 1(B) shows one complete phase of the heart's electrical activities displayed on the grid lines of the ECG. The grid lines track different intervals, such as PR, ST, and QT, which help diagnose heart disease.

3.2. Heart diseases

This section gives background information about Abn-HB, MI, and His-MI, the heart diseases analyzed in this study. A brief medical description for each of these heart conditions is given next.

Abnormal heartbeat (Abn-HB): a heart condition in which the heart beats too fast, too slowly, or irregularly. They can be caused by

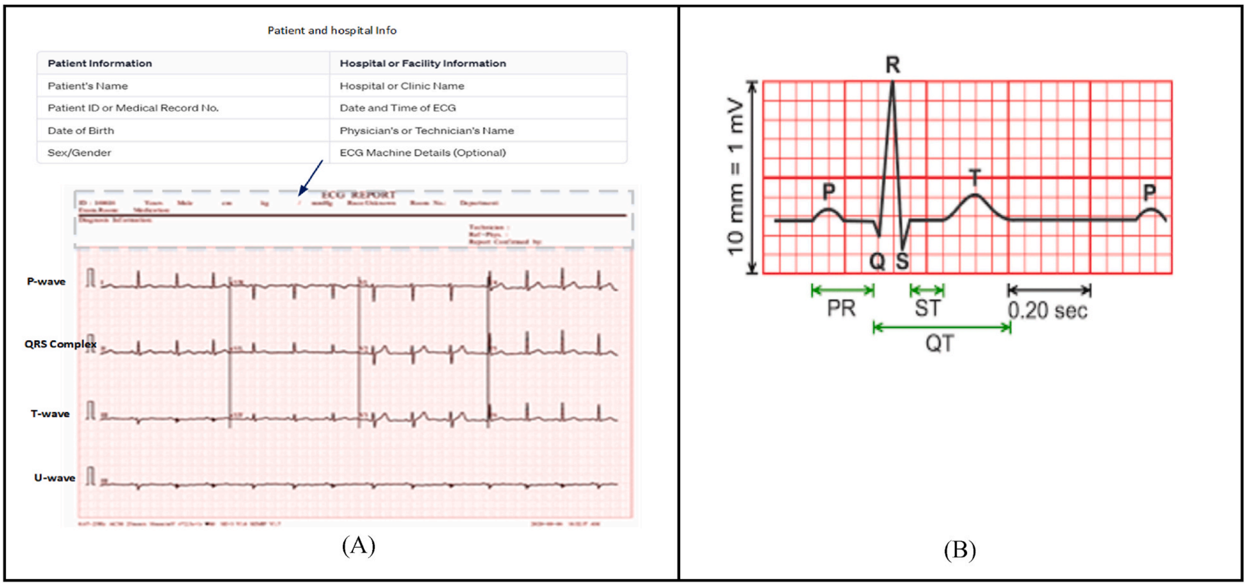


Fig. 1. (A) ECG image for a healthy patient; (B) Cardiac activities depicted on an ECG reference grid line with delineation of the respective intervals.

various factors, including structural problems with the heart, changes in the electrical conduction system of the heart, and underlying medical conditions such as high blood pressure, diabetes, and sleep apnea.

Myocardial infarction (MI): is a serious medical condition that occurs when the blood flows to a blocked part of the heart, known as a heart attack. This can cause the heart muscle to die, leading to serious damage to the heart and potentially life-threatening complications.

History of myocardial infarction (His-MI): a heart that has previously experienced a heart attack or MI. Patients with a His-MI may be at increased risk for recurrent heart attacks, heart failure, arrhythmias (abnormal heart rhythms), and other complications. Recurrent heart attacks, or His-MI, can cause lasting damage to the heart and increase the risk of future heart problems.

Cardiovascular disease (CVD), is listed as the underlying cause of death in the United States (US) [42]. According to data from 2005 to 2014, the estimated annual incidence of heart attack in the US was 605,000 new attacks and 200,000 recurrent attacks [43]. Between 2015 and 2018, 126.9 million US adults had some form of CVD [44], approximately, every 40 s, someone in the US had a myocardial infarction.

3.3. Artificial Neural Networks (ANNs)

An artificial neural network consists of three basic segments: an input layer, hidden layers, and an output layer. The input layer receives data from outside sources; the data then passes through each successive hidden layer until it reaches the output layer, where the final results are produced for interpretation. ANNs comprise a series of interconnected nodes (units) called artificial neurons (AN). AN has three main parts: "*Inputs*," to input the data to the neuron; "*Weights*," a number that determines how much influence each input has on the output; and "*Activation Function*," the mathematical function that transforms the inputs into outputs. Multiple iterations, called "epochs," of feedforward and backpropagation are executed during training. Feedforward is the process of calculating the prediction value, while backpropagation is the process of adjusting the weights of ANNs to minimize the prediction error. ANNs have various tuning parameters, such as the number of hidden layers, number of neurons per layer, type of activation function, learning rate, batch size, and epochs. These hyperparameters can be tuned to gain higher prediction accuracy. The model that achieves the highest score on the validation data is then tested on a separate dataset to assess the performance measure.

3.4. Convolutional Neural Networks (CNNs)

CNNs consist of two main phases: feature extraction and learning. Next, background information for these two phases is provided.

- *Feature Extraction Phase (FEP)*

The process of extracting useful information from data is called "feature extraction." The first step in extracting features is to divide the image into small squares, or "kernels." The kernels move across the image, and at each location, they calculate values corresponding to the image's essential characteristics. The feature extraction goes through layers; the first layer extracts basic features from the input image, such as edges and corners. The second layer builds on these features to create more complex features like shapes and textures. This process continues until the final layer recognizes a unique feature in the image.

- *Learning Phase (LP)*

LP is a normal ANN activated after flattening the extracted feature from FEP. CNNs have several hyperparameters that can be adjusted to improve learning performance. The most important hyperparameters for CNNs are the number of filters, filter size, stride, padding, pooling, dropout, activation functions, learning rate, batch size, and epochs. Training and validation losses are used to assess the performance of CNNs. Training loss measures the difference between the predicted outputs of the model and the true target values for the training examples. Validation loss measures the model's performance on a validation set obtained by comparing the predictions' accuracy between predicted and actual labels.

3.5. Visual Geometry Group 16 (VGG16)

The VGG at Oxford University created the deep learning model VGG16, a 16-layer deep CNNs. The "feature extraction" phase of VGG16 can be applied to extract features from images; the feature can then be input to any ML algorithm. The architecture of VGG16 includes 13 convolutional layers, 5 max-pooling layers, and 3 fully-connected layers. These layers are organized into six main stages, each consisting of a convolutional layer, a max-pooling layer, and a fully connected layer. The model has an input size of 224×224 with 3 RGB channels and generates 1000 features as output.

3.6. Measurement and performance evaluation methods

There are various techniques, each with strengths and weaknesses. The following evaluation metrics are used for this study.

3.6.1. Training and validation losses

There are two types of ML losses: training and validation losses. The training loss is the error the algorithm experiences while learning from the data. It provides information on how well our model parameters fit the data. However, it does not tell us how well our model performs on a new data point. The validation loss gauges how close our model is to correctly predicting labels on a different dataset. In other words, it indicates whether the model has an overfitting or underfitting problem.

3.6.2. *Confusion matrix*

A confusion matrix is a table that measures classification accuracy by contrasting actual values with expected ones. The x-axis and y-axis of the confusion matrix are labeled as actual and predicted values, respectively. The confusion matrix uses the following notations: *true-positive* (T_p) (an instance that was positive and was correctly classified as positive by the model); *false-positive* (F_p) (an instance that was actually negative but was incorrectly classified as positive by the model); *true-negative* (T_n) (an instance that was actually negative and was correctly classified as negative by the model); *false-negative* (F_n) (an instance that was actually positive but was incorrectly classified as negative by the model).

3.6.3. *The probability Density Function (PDF)*

Kernel density estimator (KDE) is a method of estimating the probability density function (PDF) from a finite dataset. KDE is a non-parametric method used in this study to display the prediction probability of the models. KDE is similar to histograms but utilizes other properties, such as smoothness or continuity, using the right kernel. If the shape of the curve tends to be narrower with less and less overlapped area in the middle, this indicates that the model correctly predicts the class with a high degree of confidence. This indicates that the model is likely to perform well on new unseen data, and provides evidence that the model has captured the underlying patterns in the data.

4. Methodology

4.1. *Dataset description*

This work uses an ECG image dataset of cardiac patients created under the auspices of the Ch. Pervaiz Elahi Institute of Cardiology in Multan, Pakistan. The publisher is Mendeley Data [45] and can be downloaded from Ref. [46].

Table 1 displays a dataset consisting of 928 ECG heart reports presented as images, classified into four distinct heart conditions: 1) normal heart conditions; 2) myocardial infarction (MI); 3) abnormal heartbeat (Abn-HB); and 4) history of myocardial infarction (His-MI). The ECG images have 2213 pixels in width and 1572 pixels in height, denoted as (2213, 1572) for (width, height), respectively. The notation $P_{i,j},$ is used to represent a pixel position, where $\{0, \leq i \leq w\}$, $\{0, \leq j \leq h\}$.

4.2. *Tools and techniques*

The techniques and tools used to build the cardiovascular disease classification model are described in this section.

4.2.1. *Image Augmentation (IA)*

IA is a technique used to increase the amount of data by adding slightly modified copies of already existing data. The following techniques from the IA pool are applied to the training dataset.

- *Image Resizing (IR):* is the process of adjusting an image's height and width to conform to a specific shape.
- *Horizontal flipping (HF):* the image is reflected about a vertical axis so that the left and right sides of the image are swapped.
- *Vertical flipping (VF):* the image is reflected about a horizontal axis so that the top and bottom of the image are swapped.
- *Image rotation (IR):* rotating the image around the center using various angles.
- *RGB channel normalization (RGB-CN):* RGB channel normalization is a technique used to standardize the pixel values of an RGB image. It involves transforming the pixel values of each channel (red, green, and blue) so that they have a mean of zero and a standard deviation of one. Usually, the values are coded like this (mean-red, mean-green, mean-blue) and (std-red, std-green, std-blue) [47].

Fig. 2(A) displays the order in which the aforementioned techniques are applied to training datasets. Fig. 2(B) depicts the image augmentation operations applied to the testing datasets.

4.2.2. *Image Preprocessing (IP)*

Image preparation involves applying various techniques to images to enhance the learning process and improve the model's accuracy. In this study, the following image preparation techniques are applied.

Table 1
ECG image dataset.

	Normal Patients	Myocardial Infarction	Abnormal Heartbeat	History of MI
Number of images	284	239	233	172

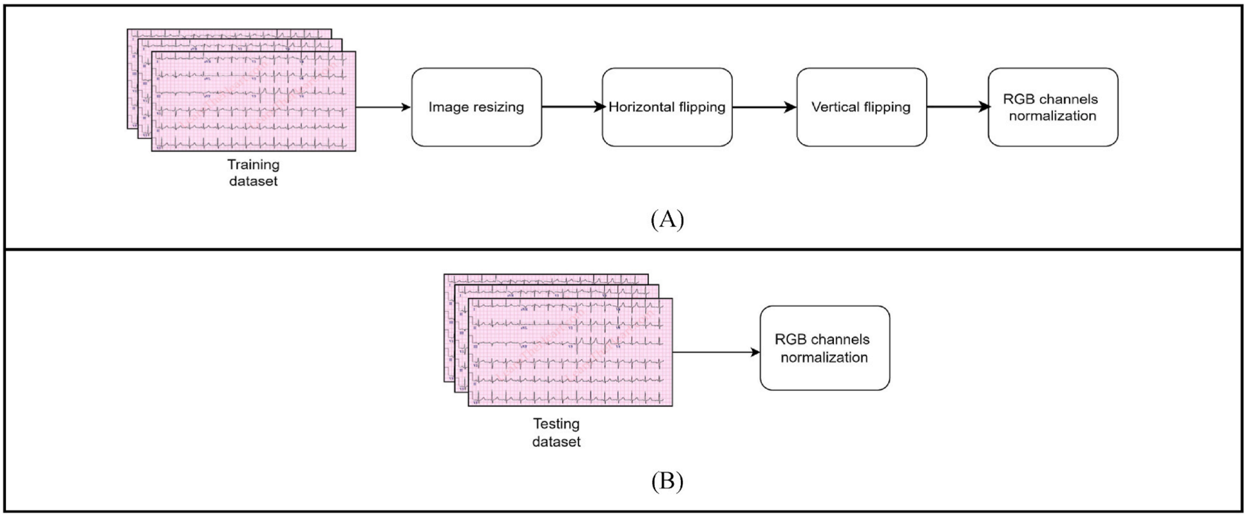


Fig. 2. (A) Image augmentation order applied to the training dataset, (B) Image augmentation order applied to the testing dataset.

- *Image cropping (IC):* remove unneeded portions of the ECG image, such as the white margin and hospital and patient information.
- *Background removal (BR):* Removing the background from an image can be helpful to the algorithm in focusing attention on the subject of interest.

4.3. Methods for developing heart disease classification models

In this study, three approaches have been tested to create a cardiovascular disease classification model. Each approach applies different techniques and tools. Three unique and standalone approaches have been employed to develop predictive models for cardiovascular diseases. Approaches 1 and 2 were utilized as benchmark points to evaluate the performance of the novel image-vectorization method under investigation. Once the performance of image-vectorization has been evaluated relative to Approaches 1 and 2, we discuss its strengths and weaknesses. Fig. 3 shows how the three approaches are conducted.

In all approaches, the ECG data is split into two datasets: a training set comprising 70 % of the data and a testing set comprising the remaining 30 %. To avoid the overfitting problem three techniques are applied: 1) A small portion (0.1 %) of the training set is further set aside for the validation dataset. 2) k-fold cross-validation (training and validating on different subsets of the data) is used to ensure the model doesn't overfit to a specific part of the dataset. 3) applying dropout rate. As explained, each approach applies some methods and techniques to create a heart disease prediction model. The accuracies of the created models, **M-Appr-1**, **M-Appr-2**, **and M-Appr-3**, are assessed using the testing dataset. The following sections explain the details of the tools and techniques used in each approach.

4.3.1. Approach 1

Fig. 4 shows the components and the operation sequence executed in Approach 1. The data is initially split into training and testing datasets. For the training dataset portion, *IA-Tr* (image augmentation for training) is applied. IA-Tr profile performs the following operations: *image resizing = Resize(700,400), horizontal flipping = 0.4, vertical flipping = 0.4, image rotation = 20, and RGB channel normalization = (0.70244707, 0.54624322, 0.69645334), (0.23889325, 0.28209431, 0.21625058).* The preprocessed dataset is then fed to the CNNs algorithm, which has two phases, FEP and LP.

Fig. 5 shows the hyperparameter configuration of the feature extraction phase of CNNs. The last step of FEP is the flattening function, which turns the 2D features into 1D features. FEP transforms each ECG image into a 1D vector. In this study,

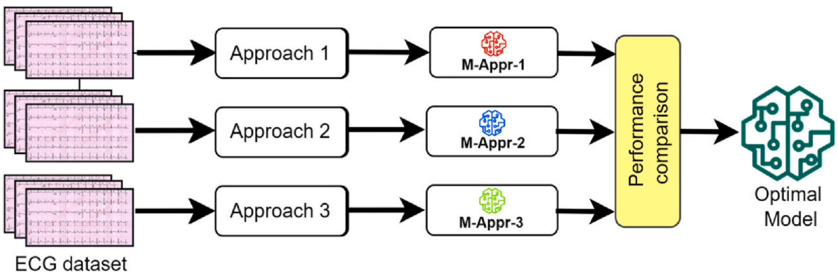


Fig. 3. Distinct approaches evaluated to create heart disease prediction model.

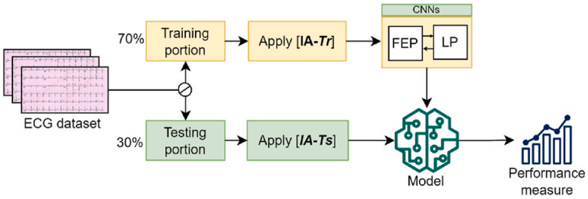


Fig. 4. Approach 1, high-level design.

$V_i(im_i), i : \{0 \leq i \leq n\}$ is used to denote the i^{th} generated vector of the i^{th} image, where n is the total augmented images during the training. $V_i(im_i)$ is then inputted into the LP of CNNs.

There are five layers in the feature extraction phase of CNNs. The following filter sizes are used in 5 layers, respectively, (3, 3), (2, 2), (3, 3), (3, 3), and (3, 3). The Rectified Linear Unit (ReLU) function is used. ReLU is a computationally efficient non-linear function that introduces non-linearity into the network, mathematically defined as $f(x) = \max(0, x)$. The fully connected neural networks of CNN's model are built using the following configuration, shown in Table 2.

CUDA is used for training CNN's model. CUDA is a parallel computing platform developed by NVIDIA. It utilizes the power of GPUs (graphical processing units) to perform highly parallel computations. The number of trainable parameters is 156227329. The optimizer Adam is used for this approach. The learning rate is set to 0.00015. After epoch = 25, the ML algorithm converges to an optimal model. The created model is then tested using the testing dataset to assess its performance. For the testing dataset, *IA-Ts* profile is applied, which comprises the following: image resizing and RGB channel normalization with the same values used for the training dataset. For future reference and analysis, the model created using Approach 1 is named **M-Appr-1**, short for "Model of Approach 1″, as depicted in Fig. 3.

4.3.2. Approach 2

As shown in Fig. 6, Approach 2 first applies image cropping, explained in Section 4.2.2, to remove unneeded portions of the ECG image, such as the white margin and hospital and patient information. The ECG dataset was cropped using the following corner values: $(x_1, y_1) = (140, 290)$ and $(x_2, y_2) = (2100, 1500)$. Hence, the new image size, after cropping is equal to (1960, 1210) representing (width, height), respectively. The cropped ECG images are passed into the VGG16 algorithm to extract features. For each ECG image, the VGG16 algorithm generates a vector $V_i(im_i), i : \{0 \leq i \leq 928\}$ that represents the i^{th} vector of the i^{th} ECG image. After applying VGG16, the vector length, $len(V_i(im_i))$, is equal to 1155585.

As explained in Section 4.1, the classes of the EGC dataset fall into four categories of heart conditions; hence, $Y_k : \{0 \leq k \leq 3\}$ is used to denote k^{th} class. By attaching the label (Y_k) to the generated feature vector, $V_i(im_i)$, from VGG16, the result is a matrix $(V_i(im_i, Y_k), i : \{0 \leq i \leq 928\}$ of 928 rows and 1155586 columns. The constructed feature matrix is then split into two sets: training and testing datasets. The validation dataset is a small portion of the training dataset (1 %). The training dataset is used to train the ANN's model, and the testing dataset is used to test the model's performance. Table 3 presents the layer configuration summary of the ANNs model. The parameter breakdown of the model is as follows: total parameters are 1015361, and the trainable parameters are 1015361. For future reference and analysis, the model created using this approach is named M-Appr-2, short for "Model of Approach 2."

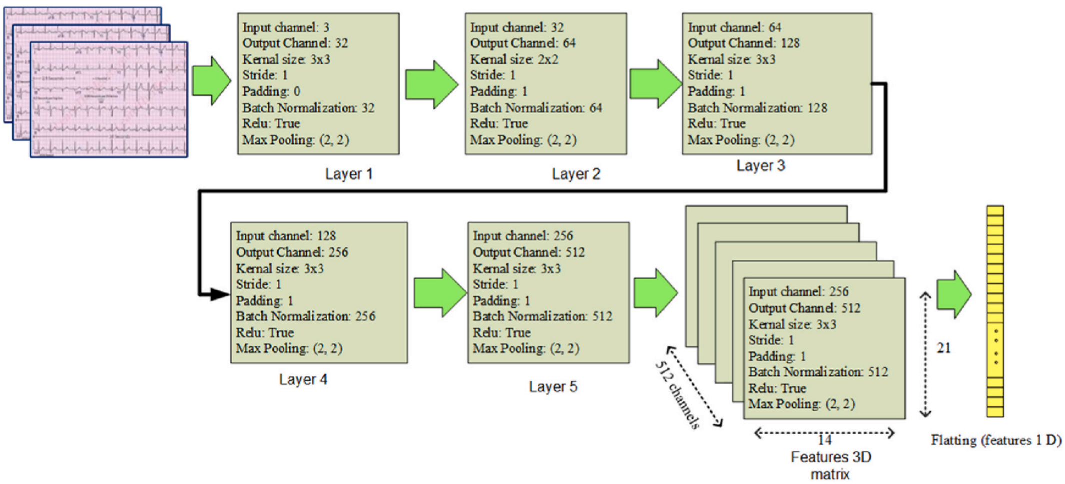


Fig. 5. Hyperparameter configurations of CNNs.

Table 2
Learning phase configuration.

Layer name	Layer type	Input feature	Output feature	Activation function	Dropout rate
Fully connected	Linear	150528	1024	ReLU	0.4
Fully connected	Linear	1024	512	ReLU	0.4
Fully connected	Linear	512	1	Softmax	–

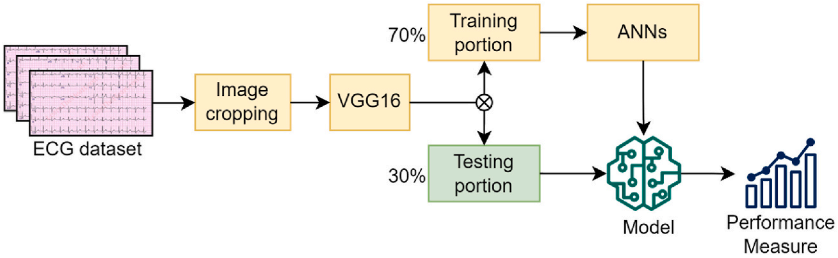


Fig. 6. Approach 2, high-level design.

Table 3
Layer configuration summary.

Layer type	Output shape	Activation function	Parameters #
Dense 0	(None, 512)	ReLu	1004032
Dense 1	(None, 20)	ReLu	10260
Dense 2	(None, 25)	ReLu	525
Dense 3	(None, 18)	ReLu	468
Dense 4	(None, 4)	Softmax	76

4.3.3. Approach 3

Fig. 7 highlights the design followed in Approach 3. First, the IP phase, outlined in Section 4.2.2, is applied to the ECG dataset. The IP stage consisted of image cropping and background removal. The implementation details of these two steps are explained next.

- *Image cropping (IC):* is used to eliminate the white margins surrounding the ECG image that contain nonessential information such as patient and hospital details (e.g., patient gender, room, date, etc.). The following corner values: $(x_1, y_1) = (140, 290)$ and $(x_2, y_2) = (2100, 1500)$ are used to remove irrelevant information. The new image size, after cropping, equals (1960, 1210), which are values for (width, height), respectively.
- *Background removal:* as explained in Section 3.1, the heart signal is displayed on grid lines used as a reference to assess the heart state conditions. ECG's grid lines are the same in all ECG images; hence, it can be considered redundant information. ML algorithms cannot distinguish patterns from similar information. The grid lines are manually removed using the following procedure:
  - Converting the ECG image to a grayscale image using "*matplotlib*" library.

$$\left(P_{ij} > \min\left(P_{ij}\right)\right) \rightarrow P_{ij} = 255 \quad (1)$$

$$\left(P_{ij} < \min\left(P_{ij}\right)\right) \rightarrow P_{ij} = 0 \quad (2)$$

In Equation (1), the algorithm first finds *min* (P_{ij}), then for every pixel in ECG image, if the return pixel value is greater than *min* (P_{ij}), assign its pixel value to the value of 255. In Equation (2), for every pixel in ECG image, if the return pixel values is less than

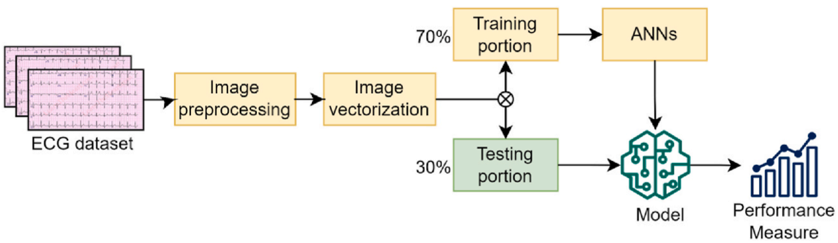


Fig. 7. Approach 3, high-level design.

$min\ (P_{ij})$, assign its pixel value to zero. Where $\forall_{ij} \in \aleph : \{0, \leq i \leq 1960\} \bigwedge \{ 0 \leq j \leq 1210\}$. $min\ (P_{ij})$ are the minimum pixel values of ECG grid lines, which were found via the pixel search function? The aforementioned procedure yields a black-and-white image, as shown in Fig. 8(A).

- *Image-vectorization (IV)*

IV is composed of two steps: column-wise summation and black-and-white pixel swapping. In black-and-white images, black pixels are typically assigned a value of 0, while white pixels are assigned a value of 255. In the black-and-white pixel swapping stage, the heart signal's pixels are given a value of 255, and the background pixels are given a value of 0, to let the ML algorithms focus attention on the heart signal rather than the background. The process of black-and-white pixel assignment is performed as follows:

$$\forall_{ij} : (i,j) \in \{heart\ signal\ pixels\} \rightarrow P_{ij} = 255 \tag{3}$$

$$\forall_{ij} : (i,j) \in \{background\ pixels\} \rightarrow P_{ij} = 0 \tag{4}$$

In Equation (3), assign all heart signal pixels to the value of 255. In Equation (4), assign all Background pixels to the value of zero. Where $\forall_{ij} \in \aleph : \{0, \leq i \leq 1960\} \bigwedge \{ 0 \leq j \leq 1210\}$. Fig. 8(B) shows a sample of the image after pixel intensity swapping.

As explained in Section 3.1, the ECG image has four horizontal lines: *P-wave*, QRS complex, *T-wave*, and *U-wave*. The output of black-and-white pixel swapping, shown in Fig. 8(B)–is then inputted into column-wise summation, which is performed using Equation (5):

$$V_i(im_i) = \sum C_n(im_i)\ such\ that \tag{5}$$

$$\forall_{in} \in \aleph : \{0 \leq i \leq 928\} \bigwedge \{0 \leq n \leq 1960\}$$

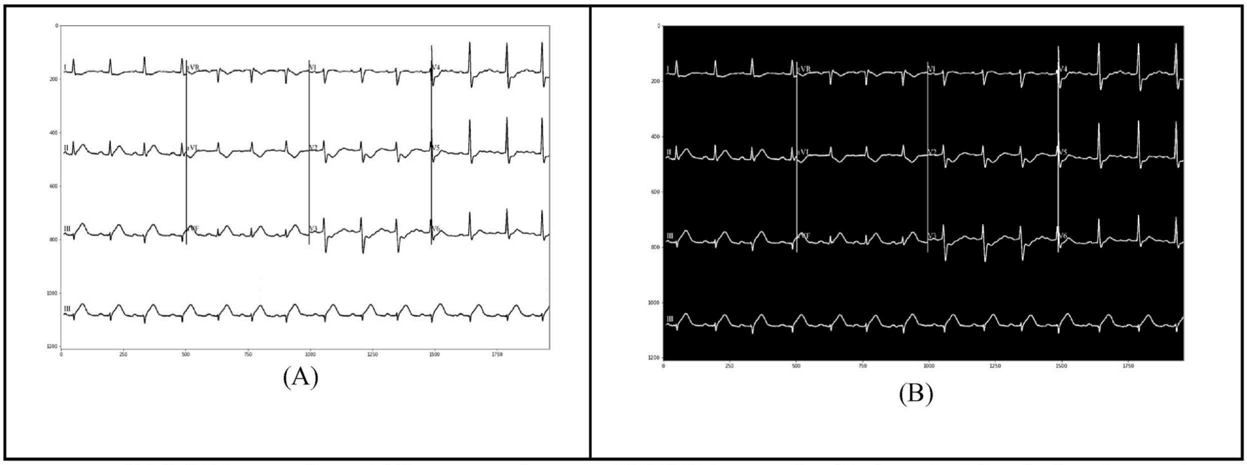
Where C_n denotes the sum of the n^{th} column of the processed i^{th} ECG image. $V_i(im_i) : \{0 \leq i \leq 928\}$ where $V_i(-)$ represents i^{th} vector of the $im_{i^{th}}$ image, 928 is the number of ECG images in the dataset. Attaching the label $Y_k : \{ 0 \leq k \leq 3\}$, k is the number of classes of the heart conditions. The result is a matrix $(928, len(V_i(im_i) + 1)$, that is $(928, 1961)$.

Fig. 9(A) displays the comparison of the vectorized normal ECG patient with MI; Fig. 9(B), normal with abnormal heartbeat; Fig. 9 (C) displays the vectorized normal patient with a patient with a history of MI; and Fig. 9(D) displays the plotting of the four vectorized EGC images. It is noticeable that the four heart conditions have distinct patterns.

The vectorization process involves transforming ECG images into a more compact vector form, effectively capturing essential features while reducing data complexity. The generated feature vector from the ECG image of different heart diseases showed distinguishable characteristics of different heart disease classes, this helps ML algorithms to capture different patterns of different heart diseases. Fig. 10 shows the correlation coefficient, which measures the strength of the relationship between two variables for the four heart conditions after ECG image-vectorization. As shown in Fig. 10, the normal heart signal has a moderately strong positive correlation with His-MI, myocardial, and Abn. HB.

As shown in Fig. 7, the vectorized matrix, $(928, 1961)$, then, is split into training and testing datasets. The training dataset is used to train the ANNs model using model configuration shown in Table 4.

As depicted in Fig. 11, four models are created for different cardiac classification tasks. The first model distinguishes between a normal heart and MI. The second model distinguishes a normal heart from one that has a His-MI. The third model differentiates between normal and Abn-HB. The fourth model is trained using the four heart condition classes. This model predicts whether a given



(A) ECG image after grid line removal; (B) ECG image after black-and-white pixel assignments

Fig. 8. (A) ECG image after grid line removal; (B) ECG image after black-and-white pixel assignments.

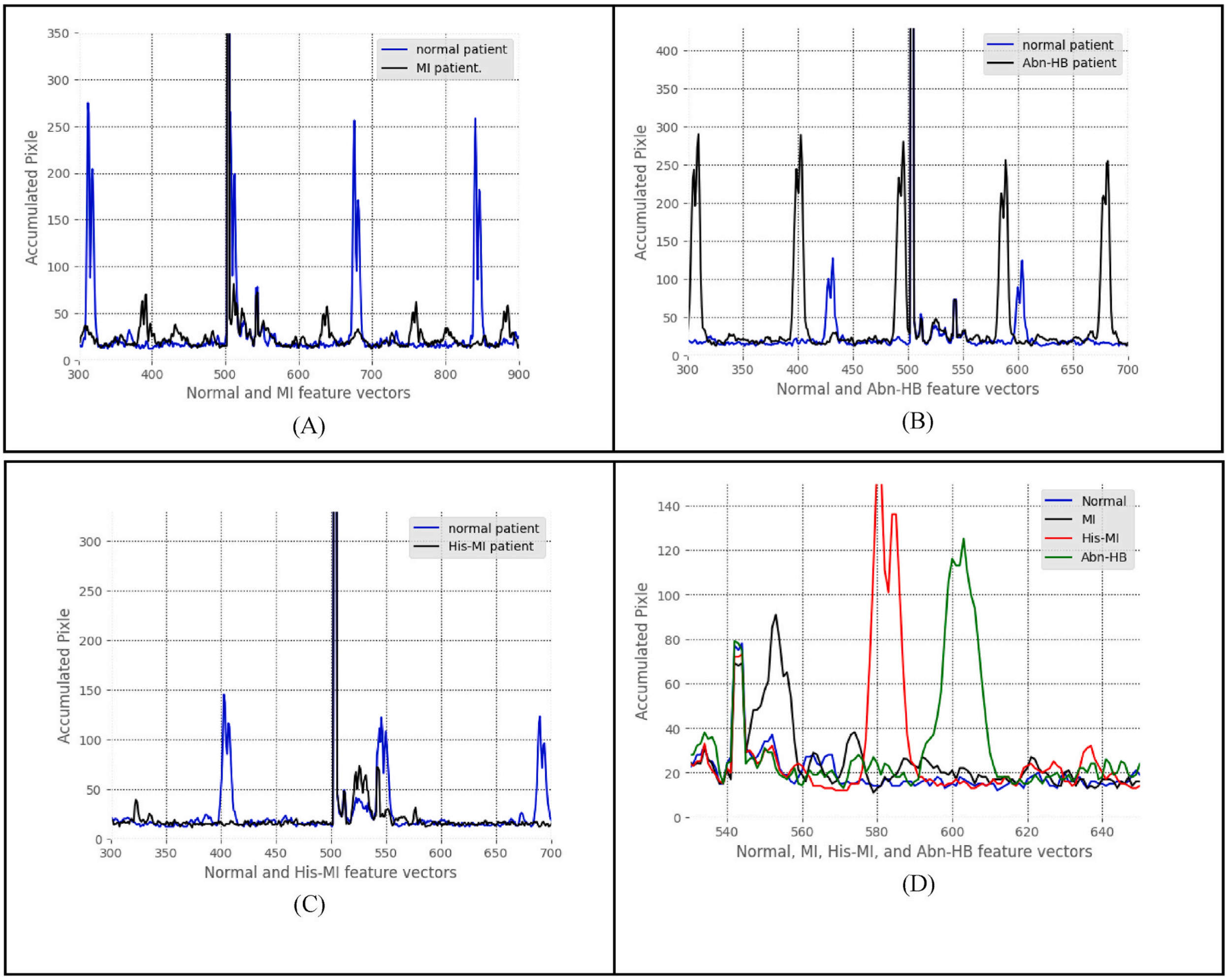


Fig. 9. Comparative vector analysis: (A) Normal vs. MI; (B) Normal vs. Abn-His; (C) Normal vs. His-MI; (D) One random sample selected from each vectorized dataset.

	Normal	MI	His-MI	Abn-HB
Normal	1	0.67	0.5	0.6
MI	0.67	1	0.73	0.73
His-MI	0.5	0.73	1	0.56
Abn-HB	0.6	0.73	0.56	1

Fig. 10. Comparative analysis of correlation coefficients among vector representations for different heart conditions.

Table 4
ANNs model structure and configuration.

Layer type	Output shape	Activation function	Parameters #
Dense 0	(None, 512)	ReLu	262144
Dense 1	(None, 20)	ReLu	10260
Dense 2	(None, 25)	ReLu	500
Dense 3	(None, 18)	ReLu	450
Dense 4	(None, 4)	Softmax	72

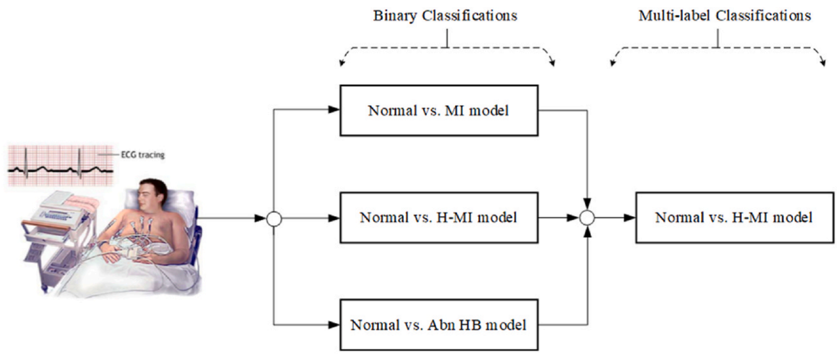


Fig. 11. Possible real implementation scenario.

cardiac condition falls into the categories of normal heart, MI, Abn-HB, or His-MI. The binary models may be applied sequentially or concurrently in actual implementation scenarios; the result is then consolidated with the four-class prediction model. The reason for applying two layers of detection is that binary classification models tend, in some scenarios, to perform better than multi-label classifications [48,49]. They also take up less memory and processing power, making them simpler to train.

5. Results

This study created a heart disease classification model. A dataset of ECG images of three different heart diseases in addition to the normal patient is used to create and test the model. To compare the advantages and disadvantages of various technologies and methods for achieving the heart disease classification model, this study employs three strategies with various system designs, as shown in Fig. 3. The results of these approaches are discussed in this section. Approach 3, using image-vectorization, achieves higher performance than the other approaches. This section provides a detailed analysis of the results obtained from the three different approaches. In Section 6, the discussion will compare and contrast these approaches based on their performance.

5.1. Approach 1

As explained in Section 4.3.1, no data preprocessing is incorporated into this approach. The original dataset is first split into two independent datasets: training and testing. Then the IA-Tr profile is applied to the training dataset, and the AI-Ts profile is applied to

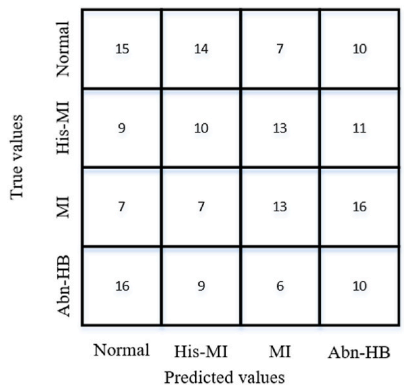


Fig. 12. The confusion matrix of M-Appr-1.

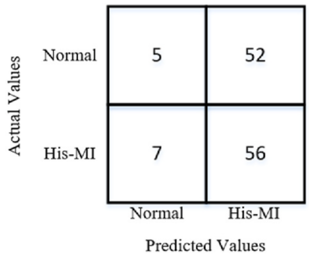


Fig. 13. Confusion matrix of binary classification using M-Appr-1.

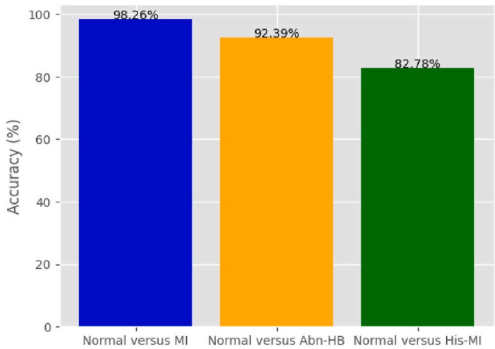


Fig. 14. Comparison of prediction performance of normal versus MI, Abn-HB, and His-MI.

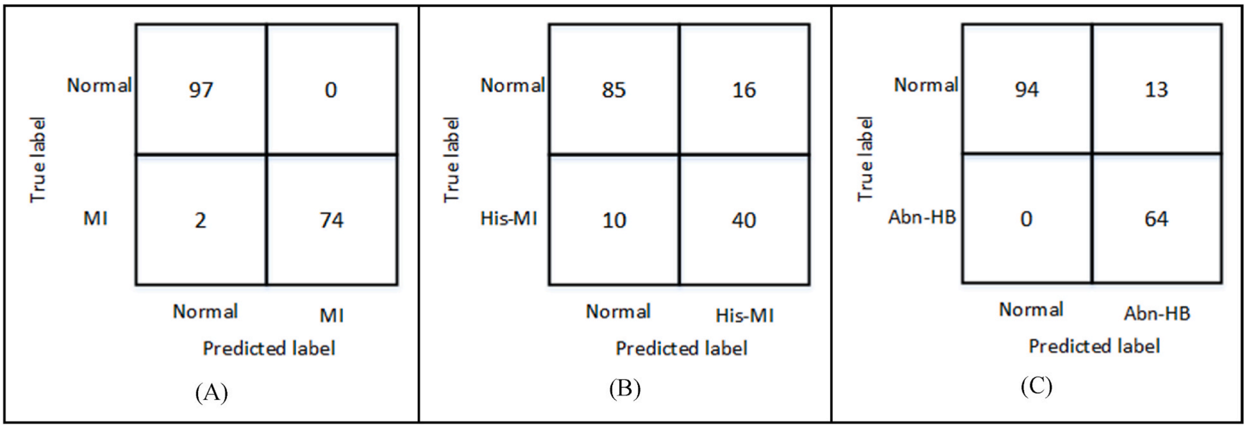


Fig. 15. Performance comparison using the confusion matrix: (A) Normal vs. MI, (B) Normal vs. His-MI, and (C) Normal vs. Abn-HB.

the testing dataset. Despite adding extra memory and computational resources via cloud computing, attaining a high-accuracy model remains challenging. The confusion matrix, shown in Fig. 12, depicts the performance of the created model (M-Appr-1) from Approach 1. Comparing the true and false classifications presented in the confusion matrix, M-Appr-1 performs close to random prediction. Poor CNNs performance on the ECG image is due to poor representation of the heart signal compared to the background. The majority of pixels in an ECG image represent the background, while a small percentage represents the heart signal itself. This imbalance shifts the focus of feature extraction toward background details, not on the heart signal features.

5.2. Approach 2

As outlined in Section 4.3.2, image cropping is implemented to eliminate noisy and repetitive information found in the ECG image, such as patient name, age, gender, etc. Keeping redundant information can introduce non-distinguishing features. Instead of using CNNs to extract features (used in Approach 1), VGG16 is used in Approach 2. VGG16 is known for its powerful feature extraction from images. Despite numerous attempts to optimize the hyperparameters, the model only attained an accuracy rate of 17.9 %. Approach 2 performs poorly compared to Approach 1 and can be considered a random prediction.

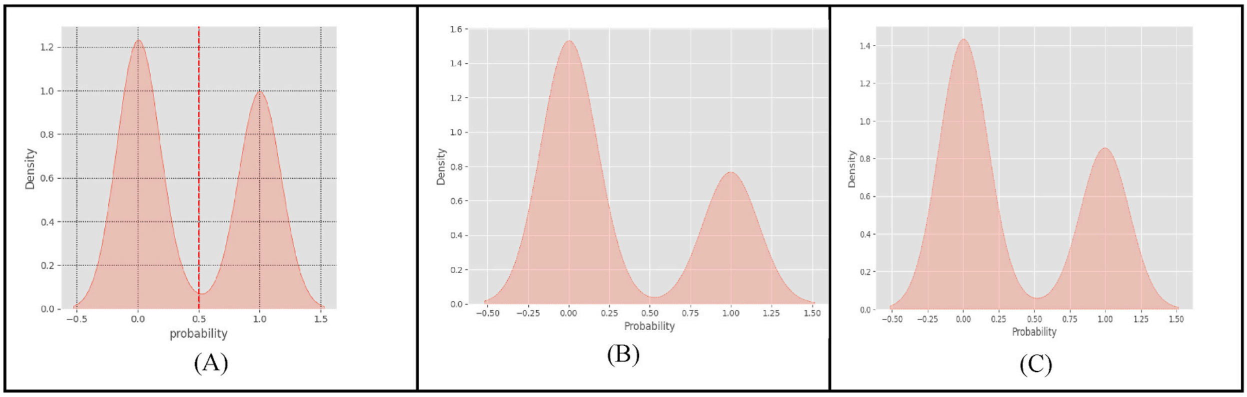


Fig. 16. Probability density function comparison for (A) normal vs. MI, (B) normal vs. His-MI, and (3) normal vs. Abn-HB.

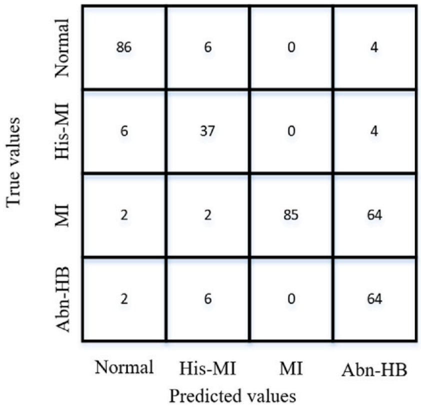


Fig. 17. Confusion matrix for multi-class classification.

Binary classification (a model trained on two classes) is taken into consideration to investigate potential alternatives for enhancing the performance of the model. M-Appr-2 is trained on two distinct datasets: normal patients and patients with MI. Fig. 13 shows the performance of the binary model. It achieves a prediction accuracy of 37.5 %. It has been observed that the M-Appr-2 model predicts normal patients as disease patients 92 % of the time.

It seems that VGG16 fails to extract various heart disease features to train the M-Appr-2 model. This might be because the extracted features by VGG16 are skewed towards the background, leading to a lack of important information about the heart signal in the extracted features.

5.3. Approach 3

As shown in Fig. 11, in Approach 3, four models are created, three are binary models, and one is a multi-label classifications model. Fig. 14 shows the prediction accuracy for each of the binary classification models: normal versus MI, normal versus Abn-HB, and normal versus His-MI. The findings show that the model for differentiating between normal and MI performs noticeably better than the models for differentiating between a healthy heart and one with a His-MI or an Abn-HB.

The performance of the three binary classification models can be further understood using a confusion matrix. The findings of this analysis are shown in Fig. 15. In Fig. 15(A), the model accurately predicts all normal heart samples, but it incorrectly classifies two samples of MI heart conditions as normal. The model performs the worst in distinguishing between normal heart conditions and a history of His-MI, with 26 samples incorrectly classified, as shown in Fig. 15(B). In Fig. 15(C), the model accurately identifies all Abn-HB, but it incorrectly classifies 13 samples of normal heart conditions as Abn-HB.

To further understand the model's prediction performance, the KDE is used. The background of KDE is explained in 3.6. Fig. 16(A) represents the PDF of the model that predicts normal vs. MI heart conditions; it shows that both classes can be predicted with a high degree of confidence. Fig. 16(B) and (C), respectively, show that when predicting normal vs. Abn-HB and normal vs. His-MI, healthy hearts were predicted with a higher degree of confidence than diseased hearts.

Fig. 17 shows the performance of the multi-label classifications model, which is trained on four different heart conditions: normal, MI, His-MI, and Abn-HB. Concerning healthy heart prediction, out of the 96 samples, 86 were correctly classified, resulting in an

Table 5
Summary of heart disease classification proposed in the literature review.

Study	ML Algorithm	ECG image Pre-processing	Features	Datasets
[6]	Hybrid CNN-Naive Bayes	Continuous wavelet transform	Independent and discriminating features	MIT-BIH Arrhythmia
[7]	MLP, SVM	DWT, DCT, CWT	P, Q, R, S, T waves	MIT-BIH Arrhythmia
[8]	GN and NN	DWT to extract features from QRS	–	MIT-BIH AR, AHA
[9]	2-D CNNs	Short-time Fourier transform	2-D spectrograms	MIT-BIH arrhythmia database
[10]	Signal processing	–	Skewness, kurtosis, shape factor, impulse factor, marginal factor, energy, root sum square, spectral entropy, energy entropy, quantile, Higuchi fractal dimension	Data collected from different hospitals
[11]	LSTM	Heartbeat extraction, signal normalization	–	UCR time series dataset archive
[12]	WT, AlexNet CNNs	–	Arrhythmia, congestive heart failure, normal sinus rhythm	MIT-BIH Arrhythmia Database, MIT-BIH Normal Sinus Rhythm Database, BIDMC Congestive Heart Failure Database
[15]	Graph Neural Networks	Sobal operator	–	MIT-BIH and PTB-XL
[16]	Back propagation neural network	Correlation, regression, temporal, morphological	–	–
[17]	LSTM	Combination of handcrafted and automatic CNNs features	–	ECG data
[18]	SVM, subtractive fuzzy clustering, neuro-fuzzy classifier	Signal processing	Skewness, kurtosis, shape factor, impulse factor, marginal factor, energy, root sum square, spectral entropy, energy entropy, quantile, Higuchi fractal dimension	ECG data collected from different hospitals
[19]	SVM	–	Coronary heart disease	Cleveland Heart Disease
[20]	SVM	Filtering and segmentation	R-R interval, QRS peak, Mean, Variance, Skewness, Wavelet coefficients, Energy, Entropy	MIT-BIH databases
[21]	Various supervised ML classifiers	Various feature selection techniques	–	UCI ML repository
[22]	Echo state network	No, low-demanding feature processing	Single ECG lead	MIT-BIH AR, AHA
[23]	2-D CNNs	No preprocessing or feature extraction/ selection	–	MIT-BIH arrhythmia benchmark database
[24]	CNNs	Not specified	Regular beat, supraventricular ectopic beat, ventricular ectopic beat, fusion beat, unknown beat	MIT-BIH ECG
[25]	CNNs	Yes	P-wave, QRS complex, T-wave	MIT-BIH
[26]	2D-CNNs	QRS detection algorithm	R peaks	MIT-BIH
[27]	KNN, DT	–	Elemental symptoms, health factors	–
[28]	CNNs, DBN, RNN, LSTM, GRU	–	Atrial fibrillation, supraventricular ectopic beats, ventricular ectopic beats	–
[29]	SVM, quadratic SVM, cubic SVM	–	–	UCI ML repository
[30]	NB, MLP, K-Star, LR, DT, J48	–	–	Cleveland Heart Disease
[31]	NB, SVM, XGBoost	–	–	ECG data
[32]	Genetic Ensemble of Classifiers	Preprocessing not specified	–	MIT-BIH Arrhythmia database
[33]	SVM, CNNs	Not specified	–	MIT-BIH Arrhythmia
[34]	RF, SVM, NB, DT	–	–	UCI dataset
[36]	1-D CNNs	WT, PCA	48 features	MIT/BI
[38]	CNNs	Preprocessing applied	–	MIT-BIH Arrhythmia, MIT-BIH Atrial Fibrillation
[39]	Deep learning methods	–	Dataset of 100,022 beats in five classes	–
[52]	–	Image denoising	–	MIT-BIH database

overall accuracy of 89.58 %. Concerning His-MI, out of the 47 samples, 37 were correctly classified, resulting in an overall accuracy of 78.72 %. For MI, out of 92 samples, 85 were correctly classified, resulting in an accuracy of 92.39 %. For Abn-HB, out of the 72 samples, 64 were correctly classified, resulting in an accuracy of 88.88 %.

As explained in Section 4.3.3. Fig. 11, in real scenarios, binary classification models are implemented first, followed by classification prediction using multi-label classifications. The two prediction results generated by the two models are examined to conclude.

Approach 3, which employs image-vectorization for heart disease classification, surpassed the benchmarks of Approaches 1 and 2. The results of Approach 1, without data preprocessing, barely exceeded random performance. The second approach, Approach 2, employing image cropping and VGG16, modestly improved binary classifications but only achieved a 17.9 % overall accuracy. Approach 3 excelled, using multiple models for classifications and achieving high accuracies—89.58 % for healthy hearts and 92.39 % for myocardial infarction. Approach 3's model demonstrated remarkable effectiveness and accuracy over the other two models.

6. Discussion

Automated heart monitoring, especially through the use of ECG, is essential in diagnosing various heart diseases. This study introduced a novel image-vectorization process for extracting heart-related features from ECG images, aimed at creating a reliable and accurate model for classifying heart disease. Table 5 summarizes the work done in the literature review of heart disease classification based on ECG analysis. The work proposed in this study enhances the challenge of heart disease classification and adds many enhancements. Here are the advantages of the image-vectorization technique over the work discussed in the literature review. 1) In-depth analysis of image-Vectorization, the latter addresses the challenge of feature imbalance, a common issue in ECG analysis. Traditional methods often struggle with the disproportionate ratio of heart signal pixels to background pixels. Image-vectorization significantly mitigates this by focusing exclusively on heart signal features. The method involves precise image cropping, removal of ECG grid lines, and strategic pixel assignment, ensuring that the heart signal is distinctly separated from the background. This detailed process not only enhances the accuracy of feature extraction but also results in a vector that is 589 times shorter than those generated by conventional models like VGG16.2) Compared to prevalent deep learning models such as VGG16 and CNNs, image-vectorization offers a more targeted approach. While traditional models extract features from both heart signals and backgrounds, our method exclusively focuses on the heart signal, thus reducing the noise from background features. This leads to a more efficient process in terms of reduced memory requirements, faster algorithm convergence [50,51], and decreased computational power, which are essential for real-time analysis and disease prediction. 3) Feature imbalance in ECG images often leads to skewed model training and can adversely affect classification accuracy. Unlike many studies reviewed in the literature, our approach explicitly addresses this imbalance. The combination of image cropping, ECG grid line removal, and pixel assignment ensures that the model is trained on more balanced features. This approach is a significant step forward in ECG image analysis, leading to improved accuracy and performance. 4) By employing a shorter vector representation, our method enables real-time analysis and prediction. The visibility of using wearable technologies combined with the proposed model in this study can offer a practical and impactful solution not extensively covered in the existing literature. This timely administration of heart health status can potentially save numerous lives and improve patient outcomes. 5) The potential of image-vectorization technique extends beyond heart disease classification, future studies could explore its application in human voice signals to extract features that can fed to ML to diagnose many diseases like Parkinson's disease, depression, and stroke.

While the image-vectorization technique marks a significant advancement in ECG analysis, it's essential to acknowledge its limitations. Future research might focus on refining the image cropping technique and exploring its integration with other ML models to enhance its applicability.

7. Conclusion

With prompt diagnosis and treatment, this study aimed to create a reliable and accurate ECG-based heart disease classification model that enhances patient outcomes. The main focus was extracting heart-related features to enable machine learning models to learn patterns and relationships specific to cardiac conditions. The proposed image-vectorization process, which included image cropping, removing the ECG grid lines, and assigning pixels to distinguish the heart signal from the background, produced a vector representation that captured the unique features of the heart signal. The proposed vector was 589 times shorter than the vector created by VGG16, which effectively reduced memory needs, improved algorithm convergence, and reduced computational power.

The experimental outcomes showed how well the created models performed in cardiac classification tasks. With better prediction accuracy, less memory usage, and less complicated training procedures, binary classification models outperformed the multi-class model. With continuous advancements in wearable technologies and the potential for real-time heart monitoring, the proposed models and feature extraction techniques have significant implications for improving patient care. The study has limitations, including a small, potentially non-diverse dataset and a focused scope on ECG Image modality. Future research should use larger, diverse datasets for better generalizability. Testing the approach in a clinical setting is needed to determine real-world effectiveness. Another envision of future work could focus on integrating the proposed image-vectorization technique and ECG-based classification model into a patient-centric system for real-time analysis and prediction of heart diseases. This could enable continuous monitoring of patient's heart conditions, alerting healthcare providers to any changes in the patient's heart signal and allowing for timely intervention. The potential benefits include improved patient outcomes, reduced healthcare costs, and increased patient satisfaction.

CRediT authorship contribution statement

AbdulAdhim Ashtaiwi: Writing – original draft. **Tarek Khalifa:** Writing – review & editing. **Omar Alirr:** Writing – review & editing.

Declaration of competing interest

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

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