Automated Classification of Myocardial Infarction using Machine Learning approaches on ECG Images

Arjun Pundir, Brahmjot Kaur

Abstract

Myocardial infarction, also known as a heart attack, is a leading cause of death worldwide. Early detection and diagnosis of myocardial infarction is crucial for effective treatment and improved patient outcomes. In this research, we propose using machine learning techniques to classify myocardial infarction using electrocardiogram (ECG) images. A dataset of ECG images will be collected and pre-processed to be used as input for various machine learning algorithms. The performance of different classification models will be evaluated using metrics such as accuracy, precision, and recall. The results of this study will contribute to the development of a reliable and efficient diagnostic tool for myocardial infarction using ECG images.

The dataset Contained four classes of Cardiovascular Diseases representing Myocardial Infarction[], Abnormal Heartbeat (Heart Arrhythmia)[] , History of Myocardial Infarction and Normal Person was divided into training and testing sets, with the former used to train the models and the latter used to evaluate their performance. A dataset of ECG signals was collected and pre-processed to be used as input for various machine learning algorithms. The images were formatted and the contour signal[] was extracted to get separate leads from each image. The obtained 13 leads data was converted into csv format to apply a variety of machine learning techniques employed in the study, including K-nearest Neighbours, random forests, and support vector machines, XG Boost Classifier and an ensembled model of all. The performance of the models was evaluated using metrics such as accuracy, precision, recall, and F1-score.

According to the experimental results, the performance metrics of the proposed ensembled model (SVM_C, SVM_gamma, KNN, Random-Forest) outperform the exiting works; it achieves 94.92% accuracy, 95% weighted average recall, 95% precision, and 95% F1 score.

In conclusion, the results of this study demonstrate that machine learning techniques can be effectively used to classify heart diseases using ECG signals. The high accuracy and other performance metrics obtained indicate that these models have the potential to be used in a clinical setting for early diagnosis and treatment of heart diseases.

Keywords: Electrocardiogram (ECG); Machine Learning; Ensembled Model; Myocardial Infarction; Cardiovascular diseases (CVDs).

1. Introduction

Heart disease is a leading cause of death worldwide. According to the World Health Organization (WHO), 17.9 million deaths occur each year due to cardiovascular diseases (CVDs), which include heart disease and stroke. Of these deaths, 85% were due to heart attack and stroke.

According to the Washington University data analytics study, people who contracted COVID-19 were 72 percent more likely to suffer from coronary artery disease, 63 percent more likely to have a heart attack, and 52 percent more likely to experience a stroke as compared to control groups. Cardiovascular disease is the leading cause of death in the United States and the world. According to the Centers for Disease Control and Prevention (CDC), approximately one in four Americans die of heart disease each year. Additionally, heart disease costs the US healthcare industry around $363 billion each year for services and medications. [https://healthitanalytics.com/news/data-analytics-points-to-cardiovascular-risk-after-covid-19]

Risk factors for heart disease include high blood pressure, high cholesterol, smoking, diabetes, and obesity. In addition, certain populations, such as those of South Asian descent, have a higher risk of developing CVDs.

A highly skilled clinician can detect heart disease from the ECG waves. However, this manual process can lead to inaccurate results and is very time-consuming [5].

There is great potential to benefit from advances in artificial intelligence in healthcare to reduce medical errors. In particular, the use of machine learning and deep learning techniques for automatic prediction of heart diseases

M. Swathy and K. Saruladha, "A comparative study of classification and prediction of Cardio-Vascular Diseases (CVD) using Machine Learning and Deep Learning techniques," ICT Express, 2021. https://doi.org/10.1016/j.icte.2021.08.021..

], [6]-[10].

The machine learning methods require an expert entity for features extraction and selection to identify the appropriate features before applying the classification phase. Feature extraction is a process of reducing the number of features in a data set by transforming or projecting the data into a new lower-dimensional feature space preserving the relevant information of the input data Early detection and prevention of heart disease can help reduce the number of deaths and disability caused by these conditions. By identifying and managing risk factors, individuals can take steps to reduce their risk of developing heart disease. This includes lifestyle changes such as eating a healthy diet, getting regular physical activity, and quitting smoking. In addition, regular check-ups and screenings can help detect heart disease in its early stages, when it is more treatable.

An electrocardiogram (ECG or EKG) is a test that records the electrical activity of the heart. It is used to diagnose and monitor a variety of heart conditions, including heart attacks, arrhythmias, and heart failure. An ECG is performed by attaching electrodes to the skin of the chest, arms, and legs. These electrodes detect the electrical activity of the heart and transmit it to a machine, which records the information on a piece of paper or a computer screen.

2. ECG Signal

The ECG image is a graphic representation of the electrical activity of the heart. It typically shows a series of waves and lines, which represent different aspects of the heart's activity.The P wave represents the electrical activity that causes the atria (the upper chambers of the heart) to contract.The QRS complex represents the electrical activity that causes the ventricles (the lower chambers of the heart) to contract.The T wave represents the electrical activity that causes the ventricles to relax.The ECG image also includes measurements that can indicate the rate and rhythm of the heart, as well as the presence of any abnormalities or problems.

In addition to the traditional ECG, there are also ambulatory ECG monitors and Holter monitors which can be worn for a period of time to record the heart's activity over a longer period of time.Overall, the ECG is a non-invasive and useful tool for identifying a wide range of heart conditions, including those which may not be apparent during a physical examination, it's a simple and low-cost method that provide a lot of information about the heart.

3. Related Works

Recent researches says that ECG can be utilized for the detection of myocardial infarction by detecting the alterations in the signals it generates. Numerous investigations (citations [24]-[27]) have been undertaken to automatically forecast cardiovascular diseases using machine learning and deep learning methodologies, exploiting ECG as a representation of image data.

The research work [12] proposes an idea to detect MI and its location using the deep learning on 12-lead ECG signals. It explained the ten geographical MI locations based on presence of MI ECG perturbations : anterior (A), anterior lateral (AL), anterior septal (AS), inferior (I), inferior lateral (IL), inferior posterior (IP), inferior posterior lateral (IPL), lateral (L), posterior (P) and posterior lateral (PL). Before sending data to CNN as input, the first ECG signals for the 12-leads are digitized at a sampling rate of 1000HZ. After that, a preprocessing method based on wavelet transformation is requested in order to reduce noise and baseline wander. These preprocessed data are segmented in order to detect R-peak. The CNN model will show ten numerical values for each 12-lead signal that will determine the probable MI locations. Usually, the Lead 2 signal is used to localize MI in the body. In this search paper, a 10-layer CNN has been used.The CNN approach that relies on 10 layers has the potential to yield precise outcomes, however, it may not be a viable solution for portable devices due to its impracticality. The reason for this is that CNN's convolutional layers that consist of numerous kernels or depths would necessitate an increased amount of computational resources.

Also, the work in [13] , ECG signal from 44 recordings of the MIT-BIH database are used to evaluate the classification performance.The ECG beats were labeled and classified in five beats types according to AAMI standards and a small patient-specific data set was used for training It proposed a CNN that consisted of three 1D convolution layers, three max pooling layers and one fully connected layer and one softmax layer. The filter size for the first and second convolutional layer was set to 5 and a stride of 2 was used for the first two max pooling layers. They achieved an accuracy rate of 92.7% in classifying ECG heart beats.

Reference [15] has shown the comparison between machine learning and deep learning methods on UCI heart disease dataset to predict two classes. In their architecture of deep learning model, they used three dense layers: the first dense layer consists of 128 neurons followed by a dropout layer of 0.2 , the second dense layer consists of 64 neurons followed by a dropout layer of 0.1 , and the third layer consists of 32 neurons. Deep learning method achieved the highest accuracy rate of 94.2%. While the machine learning methods achieved accuracy rates as: RF is 80.3%, LR is 83.31%, K-NN is 84.86%, SVM is 83.29% and DT is 82.33% by using cross validation and hyperparameter tuning.

4. Theoretical background of Machine Learning

Machine learning is a subset of artificial intelligence that enables machines to learn from data without being explicitly programmed. The theoretical foundation of machine learning can be traced back to statistical learning theory and computer science.

Statistical learning theory provides the foundation for supervised learning algorithms. In supervised learning, an algorithm learns from a labelled dataset, where the inputs are labelled with their corresponding outputs. The goal of the algorithm is to learn a mapping function from the input to the output that generalizes well to unseen data. Statistical learning theory provides the framework for analysing the generalization performance of these algorithms.

In addition to supervised learning, there are also unsupervised learning algorithms that learn from unlabelled data. These algorithms typically cluster the data into groups or learn a low-dimensional representation of the data. The theoretical foundation for unsupervised learning is less well-developed than for supervised learning, but there has been significant progress in recent years.

Reinforcement learning is another important branch of machine learning that is concerned with learning optimal decision-making policies. In reinforcement learning, an agent interacts with an environment and learns to take actions that maximize a reward signal. The theoretical foundation for reinforcement learning is rooted in dynamic programming and control theory.

Categories of Machine Learning Techniques

Supervised Learning:

Supervised learning involves learning from labelled data, where the inputs are labelled with their corresponding outputs. In other words, the algorithm is provided with a dataset where each example has a known output, and the goal is to learn a mapping function that can accurately predict the output for new, unseen inputs. Examples of supervised learning algorithms include linear regression, logistic regression, decision trees, random forests, and neural networks.

Unsupervised Learning:

Unsupervised learning involves learning from unlabeled data, where the goal is to discover underlying patterns or structures in the data. The algorithm is not given any specific output to predict, and it must find its own structure in the data. Examples of unsupervised learning algorithms include clustering, dimensionality reduction, and anomaly detection.

Reinforcement learning:

Reinforcement learning is another category of machine learning technique that is concerned with learning optimal decision-making policies. It is a type of learning where an agent interacts with an environment and learns to take actions that maximize a reward signal. The goal is to learn a policy that maximizes the cumulative reward over time.

In reinforcement learning, the agent learns from trial-and-error experience by interacting with the environment. The environment provides feedback in the form of rewards or penalties to the agent for its actions. The agent's goal is to learn a policy that takes actions that maximize the expected cumulative reward.

Reinforcement learning can be applied to a wide range of problems, such as playing games, robot control, and autonomous driving. It has also been successfully applied to real-world problems such as recommendation systems, supply chain management, and energy management.

Ensembling

Ensembling is a technique in machine learning that involves combining the predictions of multiple models to achieve better accuracy and generalization. It is a powerful technique that has been widely used in various fields of machine learning, such as image recognition, natural language processing, and financial prediction.

Ensembling can be done in many different ways, such as bagging, boosting, and stacking. Each of these methods has its own advantages and disadvantages, and the choice of method depends on the specific problem and the type of models being used.

Bagging:

Bagging, or bootstrap aggregating, is a method that involves training multiple models on different subsets of the training data. The idea is to create multiple diverse models that can capture different aspects of the data. Each model is trained independently, and the final prediction is obtained by averaging the predictions of all models. Bagging can reduce overfitting and improve the stability of the model.

Boosting:

Boosting is a method that involves training multiple models sequentially, with each model trying to correct the errors of the previous model. The idea is to create a strong model by combining multiple weak models. Boosting can improve the accuracy and reduce bias of the model.

Stacking:

Stacking is a method that involves combining multiple models by training a meta-model on the outputs of the base models. The idea is to create a model that can learn from the strengths and weaknesses of the base models. Stacking can improve the accuracy and generalization of the model.

Ensembling can be done using many different types of models, such as decision trees, neural networks, support vector machines, and regression models. The choice of models depends on the specific problem and the type of data being used.

Let Y be the target variable, X be the input features, and N be the number of base models.

The output of the ith base model for the jth instance is denoted as Mi(Xj), where i=1,2,...,N and j=1,2,...,m, where m is the number of instances in the training data.

The training set for the meta-model is denoted as {(M1(X1), M2(X1), ..., MN(X1), Y1), (M1(X2), M2(X2), ..., MN(X2), Y2), ..., (M1(Xm), M2(Xm), ..., MN(Xm), Ym)}, where each instance consists of the outputs of all the base models and the target variable.

The meta-model is denoted as f(M1, M2, ..., MN), where f is a function that takes the outputs of the base models as input and produces the final prediction.

The goal of stacking ensembling is to learn the optimal parameters of the meta-model f that minimize the prediction error on the training set. This can be achieved by minimizing the following loss function:

$$L = \Sigma i=1m\ (Yi - f(M1(Xi), M2(Xi), ..., MN(Xi)))^2$$

where Σi=1m denotes the sum over all instances in the training set.

The optimal parameters of the meta-model f can be learned using various optimization techniques, such as gradient descent, stochastic gradient descent, or L-BFGS. Once the optimal parameters are learned, the meta-model can be used to make predictions on new instances by first passing the instances through the base models to obtain their outputs, and then passing the outputs to the meta-model to obtain the final prediction

5. Methodology

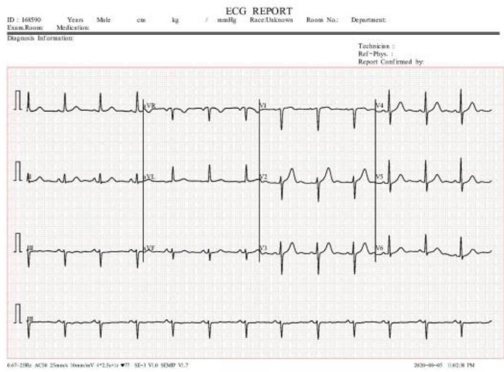
5.1 Dataset

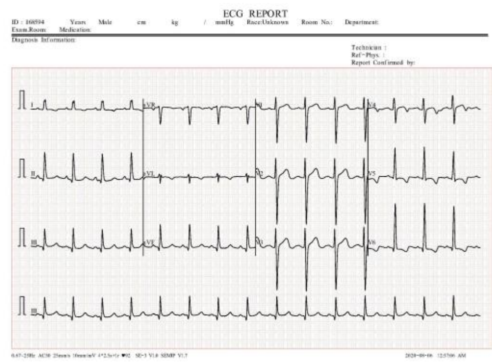
Accurately specifying the collection and gathering of data is a necessary and critical initial step. The ML methods were tested on the ECG Images dataset of cardiac patients [23]. This dataset contains 928 different patient records with four different classes. These four classes are Normal person (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI), and History of Myocardial Infarction (H. MI).

The dataset contained ECG images of Cardiac patients under the auspices of Ch.Pervaiz Elahi Institute of Cardiology Multan, Pakistan. The purpose of this organization is to foster the development of knowledge and research on Cardiovascular diseases, as well as to support the scientific community's journey towards modern advancements. The dataset of cardiac patients was published on 19 March, 2021(version 2) by Mendeley Data which is contributed by Ali Haider Khan and Muzammil Hussain [11] . The raw dataset of images can be directly downloaded from this attached link below: https://data.mendeley.com/datasets/gwbz3fsgp8/2 .

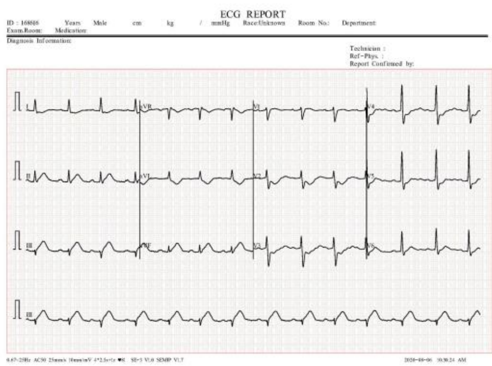
Table 1 represents the description of each ECG category in terms of symptoms, influence on the human body, and the number of ECG images in each category. The number of leads of each category are defined by 12 leads.

Category	**Description**
Myocardial Infarction (MI)	240 Images A heart attack, or myocardial infarction, is a serious medical condition that arises when the heart muscle's blood flow is impeded, usually by a blood clot. This insufficient blood flow can lead to the heart muscle's death and result in lasting damage.Immediate medical attention is essential in the event of a heart attack, as the longer the heart is deprived of oxygen, the greater the damage that occurs.It can be detected by Electrocardiogram(ECG) sensing for proper diagnosis of the patient.
Abnormal Heartbeat	233 Images An abnormal heartbeat, also known as an arrhythmia, is a condition where the heart beats irregularly or too quickly or too slowly. This can be caused by various factors, such as underlying heart disease, high blood pressure,etc. It is important to seek medical attention as early diagnosis and treatment can help prevent serious complications.They are defined in this dataset as abnormal.
Previous History of MI (PMI)	172 Images Individuals who have recently suffered from myocardial infarction (MI), heart attack, and are in the process of recuperation.
Normal	284 Images An individual who displays ordinary and predictable patterns of behavior, without any discernible abnormalities or deviations from the norm.





(a) (b)



(c) (d)

Fig. 2. Samples from the ECG images dataset.

(a) Normal person. (b) Abnormal heartbeat.

(c) Myocardial infarction. (d) History of myocardial

5.2 Pre-processing

i).Conversion of ECG images into Gray Scale.

The main goal of preprocessing is to transform the raw data into a format that is suitable for further analysis. In this particular case, we are interested in preprocessing ECG images by initially converting them into grayscale images.The ECG images are typically acquired in the RGB format, where each pixel has three color channels: red, green, and blue. However, in most cases, the color information is not necessary for ECG analysis, and we can represent the images using a single grayscale channel. Converting the images to grayscale reduces the dimensionality of the data and simplifies the subsequent analysis.

The preprocessing step for converting ECG images to grayscale can be broken down into the following sub-steps:

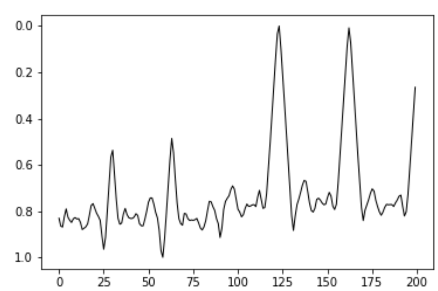
Image resizing: The ECG images may have different sizes, and we need to resize them to a common size to ensure that they are comparable.

Color space conversion: The RGB images are converted into grayscale images by using the standard formula that computes the luminance of each pixel as a weighted sum of the three color channels.

Image normalization: The pixel values of the grayscale images may need to be normalized to ensure that they have a similar range of values. This is important to ensure that the subsequent analysis is not affected by differences in image brightness or contrast.

Image enhancement: The grayscale images may benefit from image enhancement techniques such as contrast stretching or histogram equalization to improve their visual quality and make the relevant features more prominent.

By performing these preprocessing steps, we can obtain a set of standardized grayscale images that can be used as input to various machine learning or computer vision algorithms.



ii Conversion of Gray Scaled images to Binary images

Grid lines from each lead image is removed and then convert them to binary image. Conversion to binary image is done to have easy separation of the object from the background so that correct data is collected to make predictions.

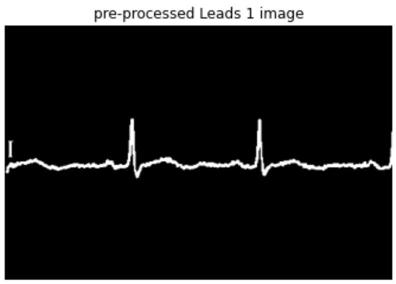
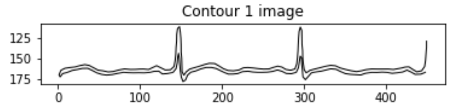


Photo black nd white lead

iii Conversion of genearted leads into contours.

Each lead corresponds to a different perspective on the heart's electrical activity, and the contours of the leads provide valuable information on the heart's function and health.

The ECG signal can be represented graphically as a waveform that shows the electrical activity of the heart over time. Each lead measures the voltage difference between two electrodes placed on the body surface, and the resulting signal is recorded as a distinct waveform. The contours of the leads are obtained by plotting the waveform as a function of time, with each lead represented by a different color.



iv Scaling and Normalization of obtained contours.

In ECG image analysis, the first step in preprocessing the images is to convert them into a one-dimensional signal. This is done by extracting the ECG waveform from each image, which represents the electrical activity of the heart over time. The ECG waveform is a continuous signal, which can be digitized by sampling it at regular intervals. This results in a one-dimensional signal, which can be easily processed and analyzed using computer-based algorithms.

Once the one-dimensional signal is obtained, the next step is to scale the signal using a normalization technique. In this case, the MinMaxScaler is used to scale the signal to a range between 0 and 1. This is done to ensure that the signal values are consistent across different ECG images and leads, making it easier to compare and analyze the data.

After scaling the signal, the next step is to extract the signal values for each lead (1-12) in all ECG images. This is done by identifying the specific lead associated with each signal and extracting the corresponding signal values. The signal values for each lead are saved in a .csv file, which is a comma-separated value file that can be easily imported into other software for further analysis.

To combine all 12 lead values with the target label added, a single csv file is created, which contains all the lead values for each ECG image, along with the target label. The target label is a binary variable that indicates whether the ECG image corresponds to a healthy or diseased heart. This label is added to the csv file to allow for supervised learning algorithms to be applied to the data.

	0	1	2	3	4	5	6	7	8	9	...	191	192	193	194	195	196	197	198	199	target
0		0.888626	0.812245	0.665561	0.500157	0.39031	0.503157	0.671016	0.831373	0.930915	0.885081	...	0.403099	0.227493	0.071006	0.036642	0.182108	0.354795	0.526547	0.687533	2
1		0.807023	0.844462	0.858971	0.862217	0.849314	0.837517	0.832122	0.804881	0.745785	0.703045	...	0.706297	0.765693	0.784813	0.795663	0.809886	0.823817	0.811508	0.79958	2
2		0.653819	0.70996	0.754838	0.81714	0.915838	1	0.95502	0.839406	0.715041	0.594235	...	0.527485	0.653147	0.777326	0.86106	0.801774	0.72608	0.689121	0.644085	2
3		0.936459	0.936513	0.94311	0.941819	0.936485	0.936999	0.947314	0.923002	0.844092	0.757641	...	0.706292	0.800846	0.852939	0.859978	0.859977	0.854643	0.853353	0.859949	2
4		0.633524	0.711548	0.790842	0.857253	0.911213	0.939912	0.934426	0.894882	0.812718	0.706587	...	0.747938	0.84287	0.89864	0.907277	0.872172	0.810854	0.739755	0.65959	2
...		...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
487		0.899701	0.925065	0.953176	0.970737	0.97288	0.987581	0.999396	0.947425	0.817473	0.682324	...	0.715492	0.843744	0.931497	0.928955	0.914313	0.918867	0.894579	0.864759	3
488		0.882043	0.903099	0.954086	1	0.982167	0.943872	0.910847	0.907839	0.912979	0.901471	...	0.859483	0.852511	0.853891	0.883268	0.926698	0.945426	0.89719	0.851191	3
489		0.792318	0.805	0.787662	0.767232	0.802106	0.861793	0.868489	0.819355	0.766635	0.748084	...	0.726346	0.774266	0.825273	0.802655	0.740945	0.72379	0.751791	0.762488	3

Normalized Contour Data obtained after Scaling

5.3 Dimensionality Reduction using PCA

PCA (Principal Component Analysis) is a widely used technique for dimensionality reduction in machine learning. The mathematical equations behind PCA are as follows:

Let X be an n x d matrix of n instances with d features each. The goal of PCA is to transform the data into a new coordinate system where the data is represented with fewer dimensions while retaining as much of the variance as possible.

The first step in PCA is to center the data by subtracting the mean from each feature. This is done by calculating the mean of each feature:

$$\mu = (\mu 1, \mu 2, ..., \mu d) = (1/n)\ \Sigma i{=}1n\ xi$$

and subtracting it from each instance:

$$xi' = xi - \mu$$

The covariance matrix of the centered data is then calculated as:

$$C = (1/n)\ X'X$$

where X' is the transpose of the centered data matrix X.

The eigenvectors and eigenvalues of the covariance matrix C are then calculated. The eigenvectors represent the directions of maximum variance in the data, and the corresponding eigenvalues represent the amount of variance explained by each eigenvector.

The eigenvectors and eigenvalues can be calculated using the eigenvalue decomposition of C:

$$C = V\Lambda V'$$

where V is a d x d matrix of eigenvectors, and Λ is a diagonal matrix of eigenvalues.

The eigenvectors are sorted in descending order of their corresponding eigenvalues, and the first k eigenvectors are selected to form a new d x k transformation matrix W.

The original data can then be transformed into the new coordinate system by multiplying it by the transformation matrix:

$$Z = XW$$

where Z is the transformed data matrix with n instances and k features.

The amount of variance retained by the transformation is measured by the explained variance ratio, which is the ratio of the sum of the first k eigenvalues to the sum of all eigenvalues:

$$\text{explained variance ratio} = (\Sigma i=1k\ \lambda i) / (\Sigma i=1d\ \lambda i)$$

where λi is the ith eigenvalue.

	0	1	2	3	4	5	6	7	8	9	target	
0		-0.549375	0.494565	-0.045338	1.422135	-0.268344	-1.590527	0.449342	0.875116	0.537622	-0.007312	2
1		-0.86306	-1.580209	0.514307	0.182243	-0.451672	-0.761466	-0.419687	-0.979922	-0.977254	-0.15015	2
2		-0.278309	0.626545	0.690094	-0.884929	-0.431733	1.087767	0.898435	0.482051	-0.000227	0.721407	2
3		-1.836973	-0.446914	1.372553	-0.256165	0.608453	0.087004	0.427743	-0.113751	0.104299	0.21023	2
4		-1.132701	-0.717709	0.090382	-1.262666	0.53316	0.439906	0.885697	0.572187	0.100195	-1.086943	2
...		...	...	...	...	...	...	...	...	...	...	...
487		-2.15717	-0.427223	0.292471	-1.614653	0.336949	-0.001895	0.78231	1.043056	-0.243457	-0.8456	3
488		-1.523648	-1.585517	0.4718	-1.570187	0.351871	0.258667	-0.013342	0.827453	0.109311	-0.819523	3
489		-0.200692	-0.29362	-1.00488	0.506783	1.626634	-0.473461	0.44773	0.041822	0.146146	0.037439	3
490		0.080288	0.438342	1.051315	0.642258	0.39241	-0.196922	0.539831	-0.720026	-0.312818	0.804052	3

Reduced Feature vectors after PCA

PCA can also be used for data visualization by projecting the transformed data onto the first two or three principal components, which can be plotted as a scatter plot. This can help to visualize the clusters and patterns in the data.

6. Experimental Setup

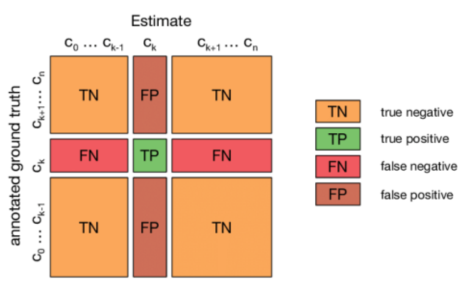
The experiments were conducted with Google Colab Pro on Intel(R) Core(TM) i5-9300H CPU @ 2.40GHz with 8GB RAM and a 4 GB NVIDIA GTX 1650 Graphics and running Windows 11 64-bit.

Preprocessing: The ECG images in the dataset contain a header and a footer information that have no relation to the features we need. Therefore, we have applied cropping for all images to focus on the valuable features. In addition, all ECG images were resized to the same resolution of 227×227 with gray scale conversion and extraction of contours from the cropped images before performing model training.

7. Performance Matrices for Classification

The performance analysis of a model involves measuring various metrics such as Accuracy, Precision, Recall, F1 score, training and testing times. These measurements are typically based on the analysis of the data presented in a confusion matrix.

The definitions of these measurements are as follows: Accuracy refers to the percentage of correctly predicted observations relative to the total number of observations. Recall represents the ratio of correctly predicted positive observations to all positive observations in the true class. Precision expresses the ratio of correctly predicted positive observations to all positive predictions in the predicted class. The F1 score is a weighted average of both Recall and Precision, taking into account both false negatives and false positives values.



Confusion Matrix

In summary, these metrics are used to assess the effectiveness of a model in accurately predicting the target class. The accuracy, recall, and precision are all important measures of model performance, and the F1 score provides a comprehensive view of model performance by considering both false negatives and false positives.

8. Results /Conclusion

Model	Accuracy	Precision	Recall	F1-Score
KNN Classifier	0.76	0.73	0.77	0.74
XG Boost Classifier	0.90	0.91	0.90	0.90
Ensembled (SVM_Gamma, Random Forest,KNN)	0.93	0.94	0.94	0.93

According to the above models tested for the given approach, best accuracy was achieved with an Ensembled model having three different classifiers that is Support Vector Machine Classifier, Random Forest Classifier and k-Nearest Neighbour Classifier.

9. References

[6] A. Rath, D. Mishra, G. Panda and S. C. Satapathy, "**Heart disease detection using deep learning methods from imbalanced ECG samples," Biomedical Signal** Processing and Control, vol. 68, no. 102820, 2021. https://doi.org/10.1016/j.bspc.2021.102820..

[7] A. Mincholé and B. Rodriguez, "Artificial intelligence for the electrocardiogram," Nature Medicine, vol. 25, no. 1, pp. 22-23, 2019. https://doi.org/10.1038/s41591-018-0306-1.

[8] A. Isin and S. Ozdalili, "Cardiac arrhythmia detection using deep learning," Procedia Computer Science, vol. 120, pp. 268-275, 2017. https://doi.org/10.1016/j.procs.2017.11.238..

[9] H. Bleijendaal, L. A. Ramos, R. R. Lopes, T. E. Verstraelen, S. W. E. Baalman, M. D. Oudkerk Pool, F. V. Y. Tjong, F. M. Melgarejo-Meseguer, J. Gimeno-Blanes, J. R. Gimeno-Blanes, A. S. Amin, M. M. Winter, H. A. Marquering, W. E. M. Kok, A. H. Zwinderman, A. A. M. Wilde and Y. M. Pinto, "Computer versus Cardiologist: Is a machine

learning algorithm able to outperform an expert in diagnosing phospholamban (PLN) p.Arg14del mutation on ECG?," Heart rhythm., vol. 18, no. 1, pp. 79-87, 2020. https://doi.org/10.1016/j.hrthm.2020.08.021.

[10] U. R. Acharya, H. Fujita, O. S. Lih, M. Adam, J. H. Tan and C. K. Chua, "Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network," Knowledge-Based Systems, vol. 132, pp. 62-71, 2017. https://doi.org/10.1016/j.knosys.2017.06.003..

[11] A. H. Khan and M. Hussain, "ECG Images dataset of Cardiac Patients," Mendeley Data, V2, 2021. https://doi.org/10.17632/gwbz3fsgp8.2.
[12] U. B. Baloglu, M. Talo, O. Yildirim, R. S. Tan, and U. R. Acharya, “Classification of myocardial infarction with multi-lead ECG signals and deep CNN,” en, Pattern Recognit. Lett., vol. 122, pp. 23–30, 2019.
[13] M. Zubair, J. Kim and . C. Yoon, "An Automated ECG Beat Classification System Using Convolutional Neural Networks," in 2016 6th International Conference on IT Convergence and Security (ICITCS), 2016. https://doi.org/10.1109/ICITCS.2016.7740310.

[14] F. Yaghouby, F. Yaghouby, A. Ayatollahi, and R. Soleimani, “Classification of cardiac abnormalities using reduced features of heart rate variability signal,” World Applied Sciences Journal.

[15] R. Bharti, A. Khamparia, M. Shabaz, G. Dhiman, S. Pande and P. Singh, "Prediction of heart disease using a combination of machine learning and deep learning," Computational Intelligence and Neuroscience, vol. 2021, 2021.https://doi.org/10.1155/2021/8387680.