ECG-BASED MULTI-CLASS HEART DISEASE CLASSIFICATION USING MULTI-LEAD FEATURES AND ENSEMBLE LEARNING

Project Submitted to the
SRM University AP, Andhra Pradesh
for the partial fulfillment of the requirements to award the degree of

Bachelor of Technology
in
Computer Science & Engineering
School of Engineering & Sciences

submitted by

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May 2025

DECLARATION

I undersigned hereby declare that the project report **ECG-Based Multi-Class Heart Disease Classification Using Multi-Lead Features and Ensemble Learning** submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology in the Computer Science & Engineering, SRM University-AP, is a bonafide work done by me under supervision of Dr Isunuri Bala Venkateswarlu. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree of any other University.

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CERTIFICATE

This is to certify that the report entitled **ECG-Based Multi-Class Heart Disease Classification Using Multi-Lead Features and Ensemble Learning** submitted by **Venkata Sravya Alapati, Sri Charan Marripudi, Gopala Krishna Parimi, Akshaya Valli Koganti** to the SRM University-AP in partial fulfillment of the requirements for the award of the Degree of Master of Technology in in is a bonafide record of the project work carried out under my/our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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ACKNOWLEDGMENT

I wish to record my indebtedness and thankfulness to all who helped me prepare this Project Report titled **ECG-Based Multi-Class Heart Disease Classification Using Multi-Lead Features and Ensemble Learning** and present it satisfactorily.

I am especially thankful for my guide and supervisor Dr Isunuri Bala Venkateswarlu in the Department of Computer Science & Engineering for giving me valuable suggestions and critical inputs in the preparation of this report. I am also thankful to Dr Murali Krishna Enduri, Head of Department of Computer Science & Engineering for encouragement.

My friends in my class have always been helpful and I am grateful to them for patiently listening to my presentations on my work related to the Project.

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ABSTRACT

Cardiovascular diseases (CVDs) are the major worldwide causes of death, and need to be diagnosed early so they would be treated effectively. Electrocardiogram (ECG) interpretation is one of the most important diagnostic tools to diagnose cardiac diseases. This project presents a framework based on machine learning designed to categorize electrocardiogram (ECG) images into four distinct classes: Normal, Abnormal, Myocardial Infarction (MI) and History of MI.

The ECG images are segmented into 13 individual leads to capture intensive cardiac activity. Preprocessing methods such as grayscale conver sion, Gaussian smoothing, and Otsu's thresholding to obtain binary images to provide more contrast in order to adequately extract features. Contour plotting is used to get the important x, y values, that are the important feature analysis of the ECG signals.

Principal Component Analysis (PCA) is employed for dimensionality reduction with important features retained. We employ a combination of machine learning classification algorithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Logistic Regression. Voting and Stacking ensemble learning Classifiers is employed in order to enhance performance and to also improve accuracy.

The system is established on the basis of robust performance indicators to reliability and robustness. The findings indicate that the multi-step process is effective in diagnosing cardiac disease, so there is an effective and scalable solution of diagnosis of cardiovascular disease and early diagnosis. The study makes contributions to the development of automated healthcare systems with earlier clinical intervention and better patient outcomes.

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Chapter 1

INTRODUCTION TO THE PROJECT

Cardiovascular disorders (CVDs) are among the top reasons for deaths globally, and millions of individuals are affected by them annually. Detection and early treatment are crucial to prevent life-threatening com- plications. Of all the methods of diagnosis, electrocardiography (ECG) is an extremely useful method for determining cardiac abnormalities. The objective of this project is to apply machine learning algorithms in ECG image analysis to properly classify heart disease.

1.1 IMPORTANCE OF CARDIAC DISEASES

Cardiovascular diseases are some of the leading causes of morbidity around the world. Sedentary life style, unhealthy diet, genetic factors, and higher age are few of the explanations for rising numbers of CVD. Detection early helps avoid severe complications like heart strokes. Effective diagnostic process and timely medical intervention can help significantly in improving the rates of survival as well as cut down on health system disbursements.

Myocardial Infarction : Myocardial Infarction (MI) refers to a condition in which the heart muscle is obstructed by a block, in the majority of instances by a clot, and thus damages the tissue. ECGs detect MI based on ST elevation, T-wave inversion, or pathological Q wave development.It is also called as heart attack.

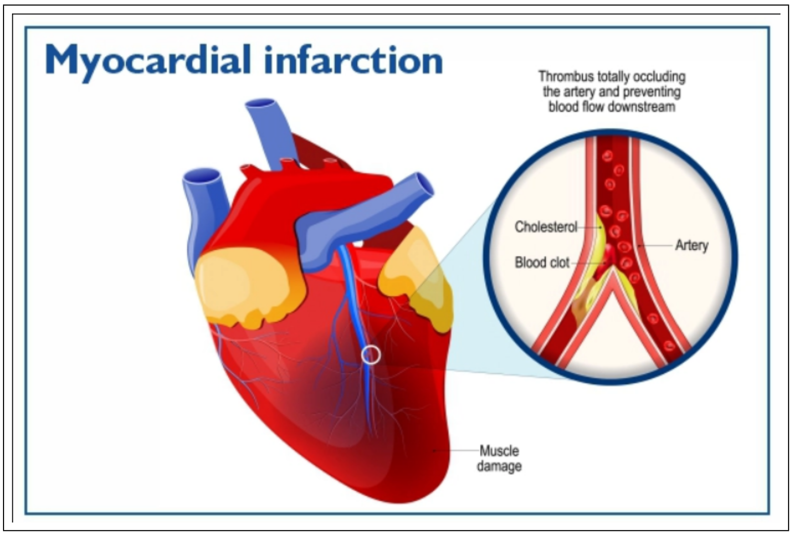

Figure 1.1: Myocardial Infarction

Abnormal Heart: An abnormal heart is plagued with problems such as abnormal rhythms, weak heart muscles, structural abnormalities, or valve problems.

Normal Heart:A normal heart is one that supplies blood well, beats regularly, and possesses healthy vessels, valves, and chambers.

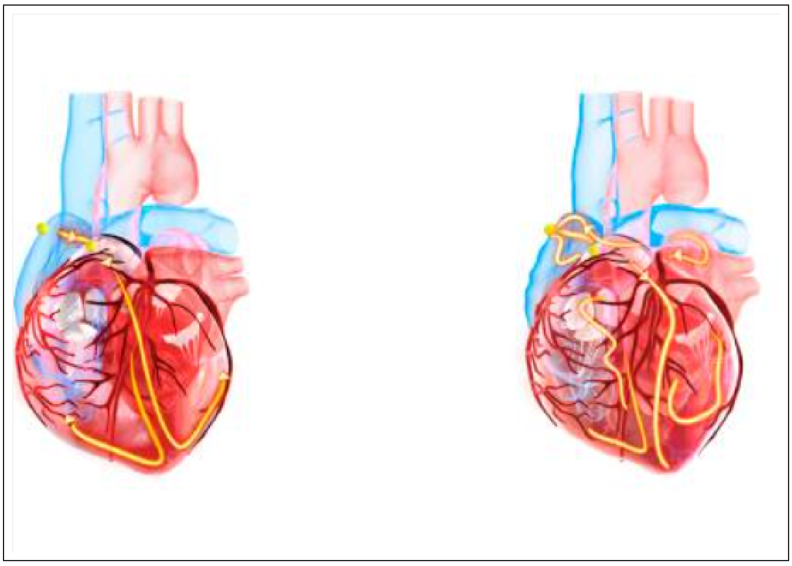

Figure 1.2: Normal and Abnormal Heart

1.2 METHODS OF CARDIAC DISEASE DIAGNOSIS

Various methods of diagnosis are used for diagnosing CVDs ranging from simple non-invasive to advanced imaging studies. Among all of them, some of the most commonly utilized advanced methods of diagnosis are echocardiography, angiography, cardiac MRI, and markers of blood. Although they give detailed information about the condition of the heart, they are utilized with the help of advanced technology and experts. Among all of them, electrocardiography (ECG) is an inexpensive and reliable tool of diagnosis since it is readily available and can yield results immediately.

1.3 WHY ECG IS USED TO DETECT CARDIAC DISEASES?

An electrocardiogram ECG is a standard diagnostic test which captures the electrical activity of the heart to identify rhythm, conduction, and general cardiac function abnormalities. It is cheap, painless, and can give immediate information regarding cardiac status. ECG is especially useful in the identification of ar-rhythmias, myocardial infarctions, and ischemia.

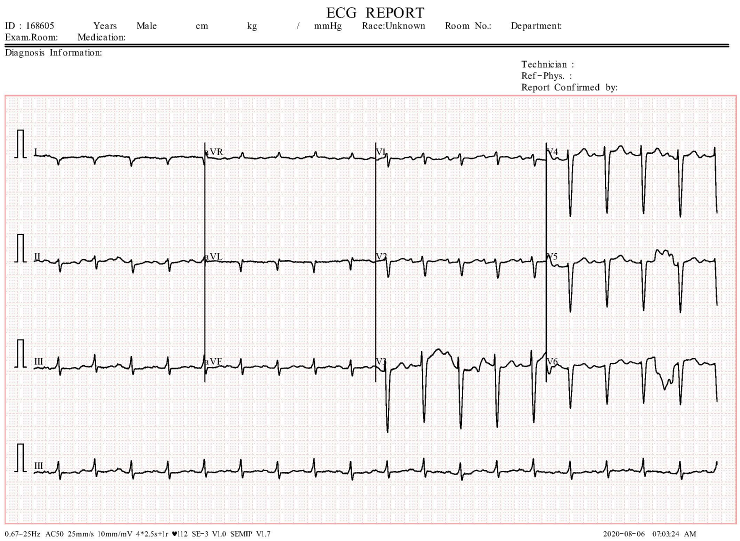

Figure 1.3: Sample ECG

Limb Leads (Frontal Plane — top view):

- Lead I Looks from right arm to left arm, shows lateral (left) view of heart's electrical activity.
- Lead II Looks from right arm to left leg, to the lower wall of the heart.
- Lead III Glances from left arm to left leg, also shows inferior wall (lower part) of heart.
- aVR (augmented Vector Right): Sees the heart from the right shoulder. Usually negative; if positive, may indicate trouble.
- aVL (augmenté Vector gauche): Looks at heart from left shoulder, views high lateral wall (upper left portion of heart).
- aVF (augmented Vector Foot): Views the heart from underneath (straight up from the legs), demonstrates the inferior (lower) surface of the heart.

Chest Leads (Transverse Plane — side/front view):

- V1: Placed over the right side of the breastbone (sternum). Views mainly the right ventricle and septum (septum is the wall of the heart that divides the right and left sides).
- V2:Also on the sternum, close to V1, is the anterior septum (anterior portion of the septum).
- V3: Between V2 and V4. Looks at the anterior wall of the heart.
- V4 Left chest, midclavicular line. Good view of anterior wall of left ventricle.
- V5: Left, same position as V4 but on anterior axillary line (side of chest). Looks at lateral wall of left ventricle.

- V6: Continue left on mid axillary line. Looks at lateral wall as well.

One more Rhythm Strip is often taken for a longer time as a rhythm strip (to look at sequential heartbeats). Occasionally a separate ”Rhythm” channel is noted on the ECG sheet, typically with Lead III.

1.4 ECG ANALYSIS AND AUTOMATION STRATEGIES

Manual interpretation of ECG is dependent on cardiologists, which is time consuming and prone to error. This has been achieved with the aid of machine learning and artificial intelligence, which perform the process effortlessly.In the project, the images of the ECG are split into 13 leads and processed with methods such as grayscale conversion, Gaussian blurring, and Otsu’s threshold to obtain binary images. Contour drawings are created to obtain feature values and dimension reduction by Principal Component Analysis (PCA). Methods such as SVM, KNN, and Logistic Regression are employed along with the complementary use of ensemble methods such as Voting Classifier and Stacking Classifier for achieving greater cardiac abnormality classification accuracy.

Chapter 2

MOTIVATION

2.1 DRIVERS OF THE PROJECT

Cardiovascular diseases (CVD's) are the world's emerging reason for deaths and early diagnosis is very important factor in successful control and prevention of death. The conventional method of diagnosis is the manual electrocardiogram (ECG) interpretation by skilled cardiologists. It is time-consuming, susceptible to human error, and even may not be possible in areas where experts are not readily available in rural or remote areas.

Machine learning and artificial intelligence technologies provide a solution with a potential to automate ECG image analysis. The technologies can provide quick, accurate, and affordable detection of heart abnormalities and allow physicians to make quick decisions. The objective of this project is to fill the gap in the delivery of healthcare by developing an effective system with a potential to diagnose heart diseases through ECG analysis. By using preprocessing methods and applying machine learning algorithms such as SVM, KNN, Voting Classifier, and Stacking Classifier, this project has a potential to improve diagnostic accuracy and facilitate timely medical intervention and thereby contributing to better patient outcomes and overall healthcare effectiveness.

2.1.1 Early Heart Disease Diagnosis

Early diagnosis of cardiovascular diseases can greatly lower the risk of major complications like heart failure or stroke. This project is associated with the use of machine learning technology for diagnosing ECG images at the correct time and in the correct way. Early diagnosis provides the time and scope of medical treatment, and that increases the time and scope of successful treatment and survival of the patient.

2.1.2 Effective and Precise Classification of Heart Diseases.

Manual processing of ECG data relies on the expertise and judgment of the medical professionals and therefore leads to inconsistent diagnosis. Preprocessing operation such as grayscale conversion, Gaussian filtering, Otsu's thresholding, and contour extraction is applied in this project to improve the quality of the image. Machine learning operation such as SVM, KNN, Voting Classifier, and Stacking Classifier are applied for precise classification of different heart diseases and therefore lead to consistent diagnosis.

2.1.3 Encouragement towards the Integration of AI into Healthcare

Use of artificial intelligence in medicine is revolutionizing the diagnostic process at a tremendous rate. The project takes the best advantage of the capability of AI in assisting in the interpretation of ECGs, saving time for the physicians, and enhancing the accuracy of the diagnosis. By streamlining minor procedures, the AI systems leave physicians free to deal with critical cases, enabling the resources and treatment to be maximized.

2.1.4 Aiding Medical Research and Practical Use

Apart from offering a concrete answer to the diagnosis of the heart, the project is also an addition to medical research. The process, outcome, and conclusion can be a foundation for more studies on medicine based on artificial intelligence. The solution can be implemented in hospitals, clinics, and telemedicine and can be used to deliver low-cost and efficient heart disease diagnosis in various environments.

Chapter 3

LITERATURE SURVEY

ECG diagnosis is the basis for cardiovascular disease (CVD) diagnosis and machine learning (ML) and deep learning (DL)[1][9] methods have been at the forefront of enhancing classification accuracy. Different ML and DL models have been explored in recent research to enhance ECG-based disease diagnosis with a focus on feature extraction, classification, and outlier detection. Mhamdi et al. [1] utilized a dataset consisting of 928 ECG images belonging to four classes of cardiac arrhythmias. MobileNet V2 and VGG16 CNN models were utilized and had validation accuracies of around 0.95. MobileNet V2 functioned best in embedded devices and is thus plausible for real-time cardiac monitoring.

Tahmid et al. [2] proposed MD-CardioNet, a 1D, 2D, and 3D feature-extracting multidimensional CNN for enhancing ECG classification. They used knowledge distillation in their approach only at the expense of giving up the high accuracy for lowering computational complexity and is deployable in real-time situations. Abubaker et al. [3] introduced a CNN classifier for ECG images using data augmentation strategies with the aim of improving generalization. They demonstrated in their project that CNNs perform better than traditional classifiers for arrhythmia, myocardial infarction, and normal sinus rhythm detection.

Mitra et al. [4] have tried deep learning networks such as DenseNet201 and InceptionV3 and achieved better classification accuracy using pre-trained networks for feature extraction. Balipa et al. [5] compared various

ML models and emphasized the significance of the feature extraction and dimensionality reduction steps for obtaining improved classification performance. They explained in their project that DL methods were better than traditional ML models in managing the variability of the ECG images.

Gulhane et al. [6] outlined transfer learning in the case of ECG classification and explained improved classification performance and how pre-trained models were transferred with ECG data, particularly when small data sets were utilized. Sakli et al. [7] experimented with the SVM performance for ECG classification, i.e., myocardial infarction case detection, and proved its effectiveness in medical applications.

Gresa et al. [8] further created a deep autoencoder method for ECG classification and demonstrated its potential for learning important features from ECG images independently and improving classification performance. Rautela et al. [9] established the scope to which the use of a mixed data set of real and synthetic ECG data improves generalizability for the model. The emphasis of their work was on using high-quality data sets to enable stable ECG classification.Bhangale et al. [10] verified that Random Forest was the best ML classifier in classifying heart disease compared to other classifiers because it utilized ensemble learning to enhance stability and reduce overfitting.

Boosting such developments, the research work conducted here presents a unique approach by segmenting the ECG images into 13 leads and employing preprocessing techniques such as grayscale conversion, Gaussian blur, Otsu's thresholding, and PCA-based feature extraction. Preprocessing removes noise, improves contrast, and maintains significant information for classification. The preprocessed ECG images are then classified into ML algorithms such as KNN, SVM, and logistic regression to further improve cardiac disease detection. Our methodology is for improved classification performance with computational optimization for improved management of enhanced and scalable diagnostics in cardiology. Based on some significant conclusions from prior research, our methodology is designed to respond to the requirements of ECG-based disease diagnosis and facilitate automated cardiac diagnostics towards real-world clinical use.

Chapter 4

DESIGN AND METHODOLOGY

4.1 DESIGN

This is an early cardiovascular disease (CVD) detection system from machine learning models based on ECG images. The process to be employed is a sequence of steps involving data gathering, preprocessing, feature extraction, dimensionality reduction, model selection, and performance evaluation. These steps are to ensure the maximum accuracy and trustworthiness of the classification.[10]

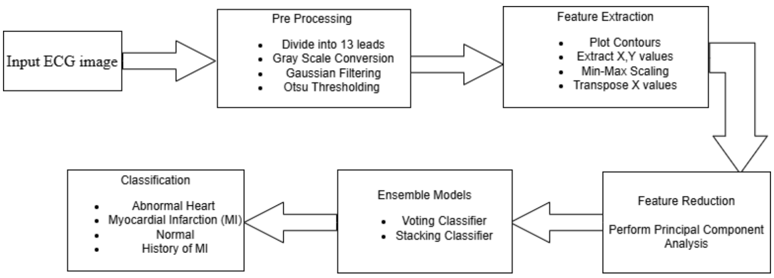

Figure 4.1: Design

4.2 METHODOLOGY

4.2.1 Data gathering

Dataset used consists of 928 ECG images of resolution 2213 X 1572 of four types:

- **Myocardial Infarction (MI)**

- **History of Myocardial Infarction (HMI)**
- **Abnormal Heart**
- **Normal Heart**

928 ECG images were used, each having 13 leads which describe multiple characteristics of the heart's electrical activity. The leads are needed in order to accurately diagnose cardiac defects.

4.2.2 Preprocessing

Preprocessing was done for the improvement of image quality and for learning discriminative features for model training. The following techniques were used:

- **Grayscale Conversion:** Grayscale conversion of the ECG images made the computation easier and reduced the computational burden.

  $$\boxed{L_{\text{gray}}(x,y) = 0.2989 \cdot R(x,y) + 0.5870 \cdot G(x,y) + 0.1140 \cdot B(x,y)}$$

  Here:

  - R,G,B are the red, green, and blue intensity of pixel (x, y)
  - $L_{\text{gray}}(x,y)$ is resulting grayscale intensity.

- **Gaussian Filtering:** The image was subjected to a Gaussian filter of appropriate kernel size for noise removal.

  $$\boxed{G(x,y) = \frac{1}{2\pi\sigma^2} \cdot \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)}$$

  Here:

- σ is the standard deviation, which determines the degree of smoothing

- **Otsu's Thresholding:** Thresholding in this adaptive mode was utilized to segment the image into white and black (binary) for contour detection.

$$\boxed{\sigma_b^2(t) = \omega_0(t) \cdot \omega_1(t) \cdot [\mu_0(t) - \mu_1(t)]^2}$$

  Here:

  - $\omega_0(t), \omega_1(t)$ are the probabilities (weights) of background and foreground classes
  - $\mu_0(t), \mu_1(t)$are mean intensities of background and foreground classes
  - $\sigma_b^2(t)$is between-class variance at threshold t

- **Creation of Binary Images:** After thresholding, clean contours were given by the resulting binary images in the extraction of lead.

4.2.3 Feature Extraction

- **Detection of Contours:** Contours were extracted by using the find Contours function of the scikit-image library, contours were detected from the binary image.

$$\boxed{\nabla I = \sqrt{\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2}}$$

  Here:

  - ∇I is the gradient of the image,
  - $\frac{\partial I}{\partial x}$ and $\frac{\partial I}{\partial y}$ are the image derivatives in the x and y directions.

- **Min-Max Scaling:** x-values and y-values were scaled to have the same range using Min-Max scaling so different leads could be compared with each other.

$$\boxed{X' = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}}$$

  Where:

  - X is the original feature value,
  - X_{min} and X_{max} are the lower and upper limits of the feature, respectively,
  - X' is the normalized feature value ,now in the range $[0,1]$.

- **X-Coordinate Extraction:** x-coordinates are the vertical plots representing amplitude that creates impact on heart disease classification .So,We neglected Y and taken X for future process.

- **Dimensionality Reduction:** Principal Component Analysis (PCA) was utilized to reduce the dimensionality of the feature space while preserving critical information. The resulting feature set compressed 255 features for each lead.

$$\boxed{Z = X \cdot W}$$

  Where:

  - X is the input feature matrix (after scaling),
  - W is the eigenvector matrix (principal components),
  - Z is the feature space with lower dimensionalty.

The eigenvectors are computed from the covariance matrix C of the features:

$$\boxed{C = \frac{1}{n} X^T X}$$

Where:

- n is the number of data points.

The study employed some machine learning models for the classification of ECG image. Models employed initially were:

- **Support Vector Machine (SVM):** SVM is an algorithm of machine learning that decides the optimal hyperplane to categorize classes by maximizing class margin and thus best suits classification for high-dimensional spaces of data.

- **K-Nearest Neighbors (KNN):**KNN predicts a new point by examining the 'k' nearest labeled points and taking into consideration the majority class among them based on distance measures such as Euclidean distance.

- **Logistic Regression:** Logistic Regression predicts a binary outcome through a sigmoid transformation, which sends any input to a probability from 0 to 1.

- **Extreme Gradient Boost (XGBoost):** XGBoost is an ensemble method which builds decision trees sequentially, one after another, with each one trying to recover from errors done by the previous ones, employing gradient boosting to achieve high speed and accuracy.

To further improve the accuracy, the ensemble models have been used:

- **Voting Classifier:** Soft voting of a collection of models' predictions.
- **Stacking Classifier:** Employed the power of ensembling numerous classifiers by aggregating their predictions to a meta-classifier (XG-Boost).

Chapter 5

IMPLEMENTATION

Implementation of the project follows a series of well-oranized steps aimed at classifying ECG images into four classes: Myocardial Infarction (MI), History of Myocardial Infarction (HMI), Abnormal Heart and Normal Heart. The step-by-step process is as follows

5.1 DATA ACQUISITION

The data set comprises 928 ECG images categorized into four classes

- Normal Heart
- Abnormal Heart
- Myocardial Infarction (MI)
- History of MI

The images are saved in individual folders. These are imported using Python libraries for processing.

5.2 LEAD EXTRACTION

- ECG images are generally made up of 13 leads that correspond to various electrical impulses of the heart.

- ECG images are visualized by plotting X and Y with the help of `Matplotlib`.The fixed coordinates are utilized to divide each lead with the help of image slicing technologies.

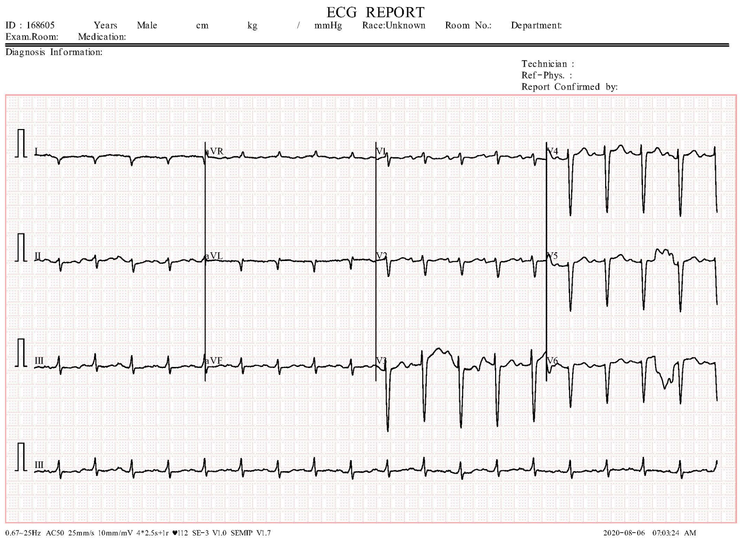

Figure 5.1: Sample ECG

- A function 'Convert_Image_Lead()' is defined to scrape and store each lead as a distinct image. This ensures each lead is dealt with separately for improved diagnosis.

Figure 5.2: Sample Leads

5.3 IMAGE PREPROCESSING

For enhancing the quality of images and pre-processing data for analysis, the following are the steps involved in preprocessing utilized:

- **Grayscale Conversion:** Grayscale conversion of ECG images is done using the `color.rgb2gray()` function. It reduces computational complexity by converting RGB images to a single intensity channel.
- **Gaussian Filtering:** Gaussian filtering with a specified standard deviation (σ) is applied using the `gaussian()` function. This step smooths the image, reduces noise, and preserves edge features.
- **Otsu's Thresholding:** A global threshold value is computed using the `threshold_otsu()` function to automatically separate the foreground (ECG waveform) from the background, producing a binarized image.
- **Binary Image:** After Gaussian Filtering and Otsu's Thresholding we will convert the image into binary image either 0 or 1 ,where 0 denotes black and 1 denotes white.We have performed Binary Imaging because it is subjected to 2 colors and highlights the area of interest (waves in ECG).

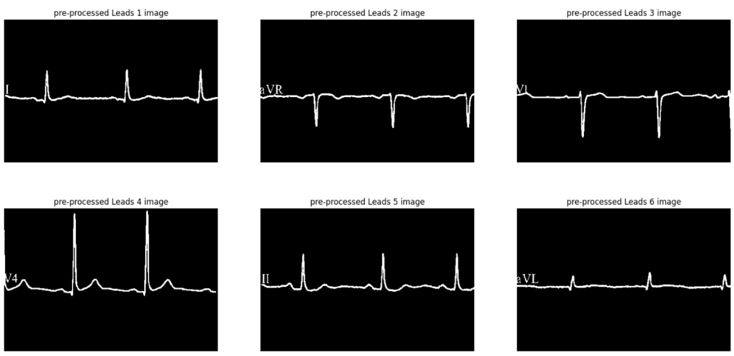

Figure 5.3: Sample Processed Leads

5.4 CONTOUR DETECTION AND FEATURE EXTRACTION

- **Contour Detection :** ‘measure.find_contours()‘ is used to detect the contour of the ECG waveforms.
- **Contour Filtering :** The largest of these contours and therefore most probable to be the actual ECG signal is taken. This is done by comparing all of their contours and then choosing the biggest one.
- **Contour Visualization :** Contours obtained after extraction in this way are graphed with ‘plt.plot()‘ to visualize it.

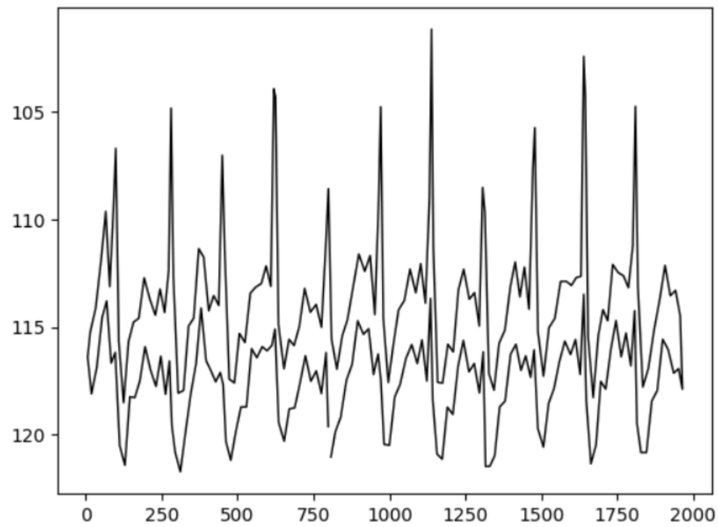

Figure 5.4: Sample Contour

- **Feature Extraction:** The (X, Y) points of the contour are saved for use later on. The extracted signal is resized into a uniform size by using ‘resize()‘ for consistency.

5.5 SCALING AND NORMALIZATION OF DATA

- Extracted features are acquired with Min-Max Scaling by ‘MinMaxScaler()‘ function.

- Scaling resizes the feature values to the range 0 to 1, facilitating model convergence and minimizing training time.

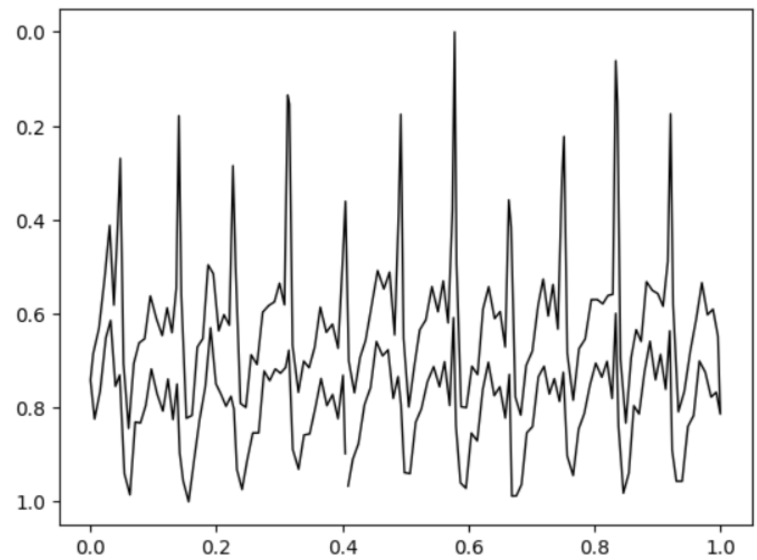

Figure 5.5: Sample Image after applying Min-Max Scaler

- Normalization of the contours were done and X coordinate values are saved into CSV files using ‘scale_csv()‘.

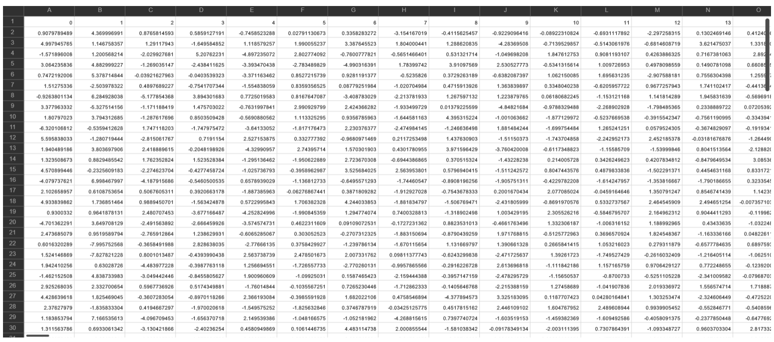

Figure 5.6: Sample Values after preprocessing,contours and scaling

5.6 CLASSIFICATION MODELS

Some of the supervised machine learning algorithms designed for classification use each of their strengths:

- **Support Vector Machine (SVM):**
  - SVM fits well with high-dimensional data.
  - It splits classes with hyperplanes, and hence it's a reliable option to classify ECG.
- **K-Nearest Neighbors (KNN):**
  - KNN is an easy-to-understand non-parametric algorithm that predicts by its nearest neighbors.
  - It is best suited to ECG classification because it is able to find patterns in the contour data.
- **Logistic Regression:**
  - Logistic Regression is used because it is interpretable and has good performance in multi-class and binary classification.
  - It is the mapping of features to target class by a logistic function.
- **XGBoost:**
  - XGBoost is an optimized version of gradient boosting that efficiently handles large data and overfitting through regularization.
  - It builds an ensemble of weak learners (decision trees in most cases) in sequence to improve model performance at high speed and accuracy.
- **Voting Classifier:**
  - A Voting Classifier accepts the prediction of multiple models and carries out a majority vote.

- It enhances precision by making the most of different models' strengths.
- We have used different models like SVM,KNN,XGBoost,LogistiRegression as base estimators

- **Stacking Classifier:**
  - Stacking trains a number of base models and combines their outputs to provide input into a meta-classifier.
  - This ensemble technique is bound to provide accuracy and robustness.We have considered different final estimators like XGBoost and SVM where we have achieved similar accuracy.

Chapter 6

HARDWARE/ SOFTWARE TOOLS USED

6.1 HARDWARE SPECIFICATIONS

6.1.1 System Configuration:

- **Processor:**Intel Core i7
- **RAM:** 8 GB
- **Storage:** At least 50 GB of disk space to store results and images.

6.2 SOFTWARE SPECIFICATIONS

6.2.1 Operating System:

- Windows 10/11, macOS, or Linux

6.2.2 Programming Language:

- Python 3.8

6.2.3 Libraries and Frameworks:

- **NumPy:** For performing numerical computation
- **Pandas:** Data Analysis and Manipulation
- **Matplotlib and Seaborn:** To visualize the data
- **Scikit-learn:** To implement machine learning algorithms

- **Scikit-Image:** For applying contour extraction and preprocessing

6.2.4 Development Environment:

- Google Colab (For coding and testing)

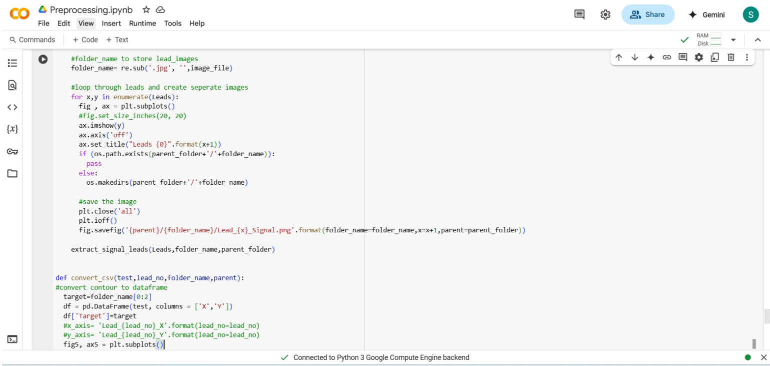

Figure 6.1: Google Colab

6.2.5 Other Tools:

- **Excel or Google Sheets:** Result reporting and analysis.

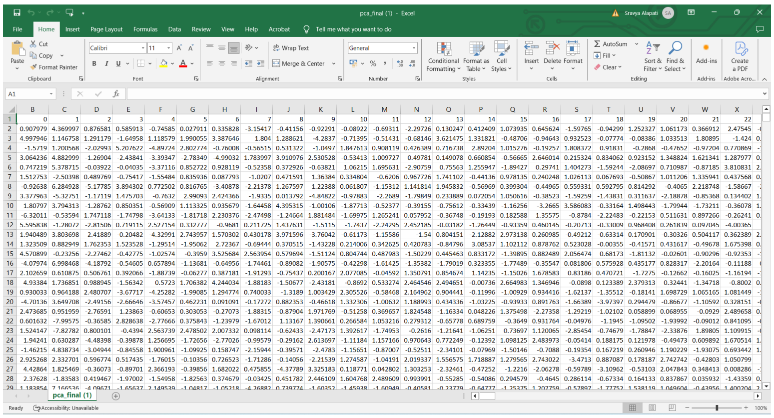

Figure 6.2: Excel

- **LaTeX (Overleaf):** Writing of report and documents All the above tools are useful in the preprocessing of the project, feature extraction, classification, and result analysis.

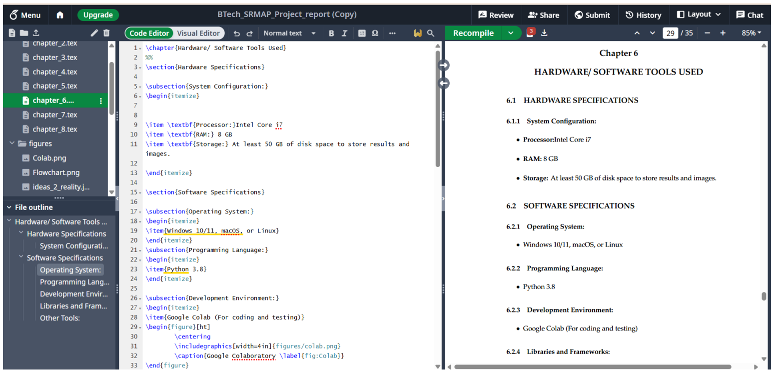

Figure 6.3: Overleaf

Chapter 7

RESULTS & DISCUSSION

7.1 RESULTS

Model Evaluation

Performance is then evaluated after the models are trained based on the following important measures

- **Accuracy:** Identifies the proportion of correctly labeled images.
- **Precision:** It measures the rate of correct positive predictions.
- **Recall:** It states the capacity of the model in identifying true positives.
- **F1-Score**: Scales precision and recall, resulting in a global measure of performance.
- **Confusion Matrix:** A confusion matrix is created in order to graph classification performance.It is also indicative of true positives, true negatives, false positives, and false negatives.
- Best-performing model is identified through comparing the measures stated above.On a basis of performance, best and most accurate and reliable model is proposed to be implemented.

Table 7.1 presents a comparison of some machine learning models used to classify ECG images. Accuracy, Precision, Recall, and F1-Score are performance metrics considered basic in evaluating the performance

Table 7.1: Model Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score
KNN	77.36	0.7779	0.7737	0.7594
Logistic Regression	88.69	0.8947	0.8869	0.8819
SVM	93.10	0.9327	0.9310	0.9302
XGBoost	93.32	0.9356	0.9332	0.9324
Voting Classifier	95.47	0.9585	0.9547	0.9536
Stacking Classifier	**98.06**	**0.9817**	**0.9806**	**0.9806**

of each model in conducting the classification task, particularly in medical imbalanced datasets where false negatives and false positives are important. The Stacking Classifier worked best with the highest accuracy of 98.06%. This suggests that stacking many classifiers and combining their decision-making can dramatically enhance classification performance.

The Voting Classifier also performed amazingly well at 95.47% accuracy, just short of stacking but far ahead of all of the base learners in isolation. Its precision (0.9585) and recall (0.9547) were both so superior that they indicate balanced performance and stable prediction for every class.

XGBoost as well as SVM, being two very good single learners, also yielded similar results with accuracy of 93.32% and 93.10% respectively. Precision and recall of both were similar at approximately 0.93, showing that both the models are strong and efficient for this task.

Logistic Regression also performed well with 88.69% accuracy, being sufficient for linearly separable data, although it lacked depth to match ensemble models in identifying intricate patterns in the ECG images.

Lastly, K-Nearest Neighbors (KNN) worked worst on all measures, with 77.36% accuracy and the lowest F1-measure of 0.7594. KNN can certainly perform well with trivial cases but poorly when faced with the high-dimensional information of the images or noised inputs, which is perhaps the reason that it worked so poorly here. In summary, this comparison affirms that ensemble learning algorithms, particularly stacking, possess many advantages over traditional classifiers to address advanced biomedical image classification challenges.

- **Voting Classifier**

Class	Precision	Recall	F1-Score
0	0.9579	0.9572	0.9572
1	1.0000	1.0000	1.0000
2	0.9062	1.0000	0.9503
3	0.9873	0.8145	0.8902
Accuracy	0.9547		
Weighted Avg	0.9585	0.9547	0.9536

Table 7.2: Performance evaluation report for Voting Classifier

- 95.47% high accuracy with excellent results in Class 1 and Class 2 with near perfect performance.Every thing is good but we can see that reduce of Recall for class 3 comparitively with previous models. So, we can use Stacking Classifier to improve recall values.

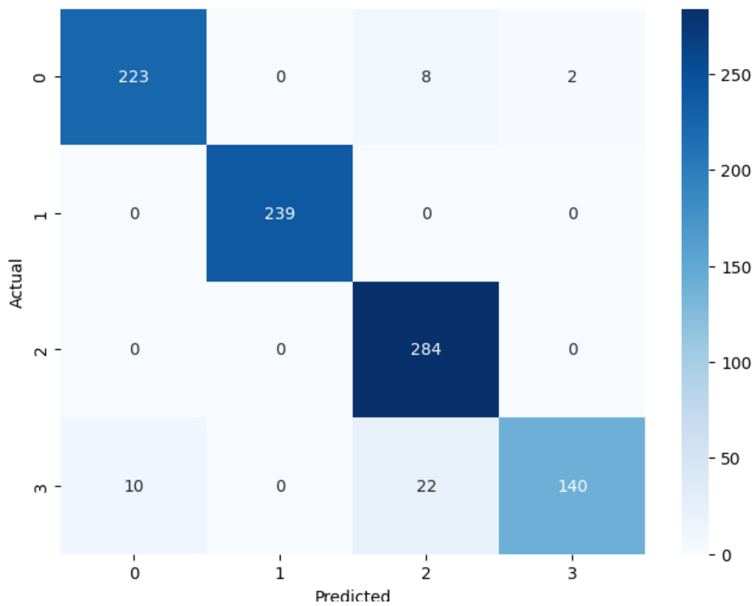

Figure 7.1: Confusion Matrix for Voting Classifier

- Minimal misclassifications, reflecting the benefits of ensemble learning probably a positive sign for us to try with one more ensemble learning Stacking Classifier.Since we are using Stratified K Fold validation results are accurate (compared to regular k-fold)

- **Stacking Classifier**

Class	Precision	Recall	F1-Score
0	1.0000	1.0000	1.0000
1	1.0000	1.0000	1.0000
2	0.9795	0.9579	0.9680
3	0.9352	0.9654	0.9487
Accuracy	0.9806		
Weighted Avg	0.9817	0.9806	0.9806

Table 7.3: Performance evaluation report for Stacking Classifier

- Highest accuracy of 98.06%, with ideal classification for Class 0 and Class 1, and good performance in Class 2 and Class 3

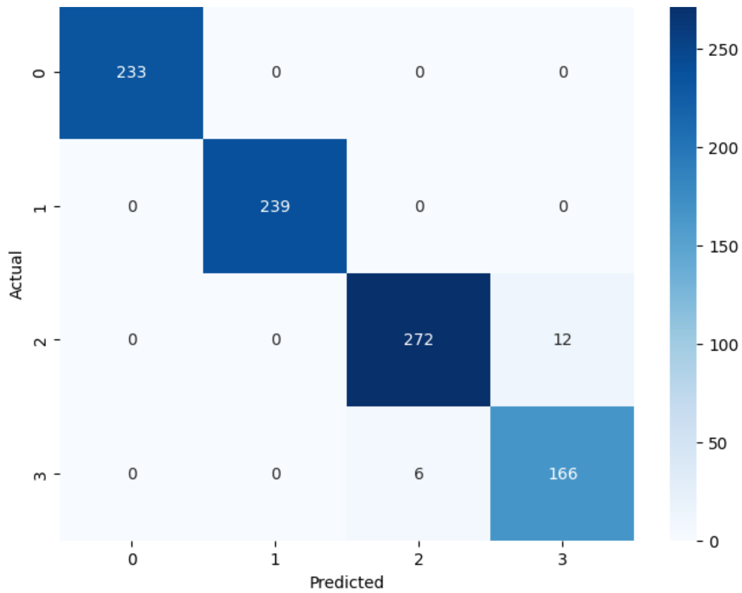

Figure 7.2: Confusion Matrix for Stacking Classifier

- Very few misclassifications, which reflects the success of model stacking.We can consider Stacking model as the best among all the models.

Table 7.4: Performance Comparison with existing models

Model	Accuracy (%)	Precision	Recall	F1-Score
Voting Classifier	95.47	0.9585	0.9547	0.9536
Stacking Classifier	**98.06**	**0.9817**	**0.9806**	**0.9806**
MobileNetV2 Transfer Learning	93.00	0.93	0.93	0.93
MobileNetV2 Fine Tuning	95.00	0.95	0.95	0.95
VGG16 Transfer Learning	91.00	0.91	0.91	0.91
VGG16 Fine Tuning	95.00	0.95	0.95	0.95
SVM	90.5			
XGBoost	85.3			

Table 7.4 demonstrates a comparison between the performance of the proposed models and the existing models in fine-grained manner. Comparison is done on four diverse metrics: Accuracy, Precision, Recall, and F1-Score.

Voting Classifier and Stacking Classifier, employed in the present study, performed better.Among them, the Stacking Classifier worked best in all the parameters where accuracy of 98.06% and remaining parameters are 0.9817,0.9806,0.9806, showing its strength and effectiveness in eliciting the strength of individual base learners. Voting Classifier also worked well with accuracy of 95.47% and equal precision and recall values, showing its reliability and stability in ECG classification task.

But models utilized in [1], such as MobileNetV2 and VGG16 based on both fine-tuning and transfer learning techniques, were found to have comparatively lower performance. Fine-tuned MobileNetV2 and VGG16 were found to possess 95.00% accuracy, which validates the efficacy of fine-tuning in transferring pre-trained models to the ECG image characteristics. In fact, their performance values lagged a bit behind ensemble models in this research study.

In addition, SVM (90.5%) and XGBoost (85.3%) of the comparative conventional machine learning models in [9], as outstanding as they were,

were surpassed by the ensemble models or deep learning-based models. The performance difference reflects the failure of traditional algorithms to deal with complex spatial and morphological patterns in ECG images.

Generally speaking, models presented in this work ,predominantly the Stacking Classifier performed superior to literature developed methods, demonstrating the power of model ensemble techniques in making classification performance achievable in cardiovascular disease detection.

7.2 DISCUSSIONS

In the current study, a few machine learning models were applied for predicting the ECG images into four classes, i.e., Myocardial Infarction (MI), History of MI, Abnormal, and Normal. Comparison between KNN vs. Logistic Regression vs. SVM vs. XGBoost vs. Voting Classifier vs. Stacking Classifier indicated interesting outcomes of their performance. We have applied Stratified K-Fold cross Validation with 5 folds for each model and compared the mean accuracy taken from those 5 folds.

The KNN model was also good, where Class 1 was correctly classified but Class 3 had misclassifications so large that the model's accuracy was 77.36%. The model's sensitivity to the data change and the model's failure to generalize were some of the reasons why the model's accuracy was low.

Logistic Regression produced a higher output with an accuracy of 88.69%. Class 1 and Class 2 could easily be differentiated, but Classes 0 and 3 were tricky since they possess the same attributes and lack good separation in the feature space.

SVM also raised the classification to 93.10% with improved class boundary formation. The ability of the model in minimizing the number of false negatives, especially for Class 2, demonstrated its ability in handling complex decision boundaries.

The XGBoost model outperformed all the other remaining classifiers at 93.32% with the strong boosting algorithm. It provided improved recall and precision to Class 0 and Class 3 by minimizing the misclassification to the least possible degree through iterative learning.

Ensemble classifiers such as the Voting Classifier and Stacking Classifier were enhanced by the combination of the best features of each of these classifiers. The Voting Classifier performed nicely at 95.47%, doing an excellent job at minimizing the misclassification of Class 0 and Class 2. The Stacking Classifier performed best overall of the classifiers at 98.06%, with the nearly perfect distinction between Class 0 and Class 1 and satisfactory classification for Class 2 and Class 3.

Generally speaking, the Stacking Classifier performed superior to the other in ECG classification, an expression of ensemble learning power applied in medical imaging. Subsequent research may include more hyperparameter tuning, addition of other feature extraction techniques, or addition of deep learning into a better approach to improve further the accuracy of classification.

Chapter 8

CONCLUSION

In this project, we set up a strong pipeline for ECG image-based heart disease classification with strong preprocessing techniques, feature extraction, machine learning classifiers and Ensemble methods. Preprocessing was important to cleanse the quality of the ECG images from noisy features and improve contrast. Techniques like grayscale conversion provided consistency, and Gaussian filtering efficiently removed high-frequency noise without discarding useful patterns of the ECG waveform. Otsu's thresholding also cleansed the image by splitting the dominant areas, thereby improving the feature extraction process. Preprocessing techniques like these were very important in cleansing the weak heart disease abnormalities present in ECG signals, improving the classification accuracy.

Feature extraction was performed by obtaining contour-based x and y coordinates from preprocessed images. Feature normalization was performed by using Min-Max scaling in a way that the features varied between fixed values, for model stability and convergence. PCA was also used in feature reduction, eliminating redundant features but retaining the important features. Apart from enhancing the efficiency of computers, this also minimized the instance of overfitting, especially for models such as SVM and XGBoost. The application of PCA was a crucial aspect in enhancing the classification performance by highlighting a significant pattern of data.

The implementation of machine learning algorithms such as KNN, logistic regression, SVM, XGBoost, and ensemble models such as Voting

Classifier and Stacking Classifier gave relative performance of various algorithms. Through use of Stratified K-Fold Cross-Validation with five folds, we ensured that we employed the same test for all the models. Although less advanced models such as KNN were unable to identify complex ECG patterns, more advanced models such as XGBoost and ensembles were more accurate. Surprisingly, the Stacking Classifier was the most accurate with an accuracy of 98.06%, through interaction of different base models. This project confirms the importance of systematic preprocessing and reducing feature dimensionality in improving model performance, and is a feasible means of automating heart disease diagnosis.

8.1 SCOPE OF FURTHER WORK

More effort in the project can come in the form of improved preprocessing techniques based on adaptive filtering and wavelet transforms, which can provide improved noise removal and improved feature extraction from ECG signals. Abnormal pattern detection can be improved further by using domain-specific signal processing techniques. More use of PCA can be for more meaningful feature extraction, dimensionality reduction with less loss of information. More dimensionality reduction techniques can be applied for facilitating improved training time and model efficiency.

Through modeling, discovery of more intricate architectures like CNNs or ViTs would improve the accuracy of classification by revealing complex temporal and spatial patterns in ECG signals. Such models like CNN-RNNs would also give better sequential analysis required by effective cardiac disease diagnosis. Moreover, incorporation of Explainable AI (XAI) methods would give model predictions interpretability to clinicians, which would develop AI-based medical diagnosis trust. Visualization interface development of model predictions would enhance clinical decision-making.

Enlargement of the dataset size with the inclusion of additional mixed ECG samples, including multi-lead data, will extrapolate model performance to varied patient populations and numerous different medical conditions. Improved data augmentation methods will provide relief from class imbalance without sacrificing model evaluation fairness. Additional exploration of rapid deployment by cloud services or edge computing can also be explored for faster diagnosis with early intervention capabilities. Easy-to-use, interactive healthcare professional interfaces can be designed to bridge the gap between AI and actionable medical use to more accurate, accessible detection of cardiac disease.

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LIST OF PUBLICATIONS

We have communicated our Journal in **International Journal of Imaging Systems and Technology**