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Detection of Myocardial Infarction Using ECG Images

[1]Dr.Buddesab [2]Bhavya Shree C S, [3]Bhuvana C Basavanand , [4]D V Veena, [5]Varsha P,

[1]Associate Professor.,[2,3,4,5]Student

[1,2,3,4,5]Department of Artificial Intelligence and Machine Learning,

[1,2,3,4,5]Cambridge Institute of technology Bangalore, India

Abstract: This paper presents an innovative approach for myocardial infarction (MI) detection through an ensemble of three distinct models: Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (CNN). Trained on labeled electrocardiogram (ECG) image datasets, each model is individually optimized for effective discrimination between MI and non-MI cases. The models' unique strengths, encompassing SVM's handling of high-dimensional feature spaces, Random Forest's ensemble learning, and CNN's proficiency in hierarchical feature extraction, are strategically combined through the AdaBoost ensemble method. The resulting ensemble model is rigorously evaluated on a separate set of ECG images, demonstrating its enhanced diagnostic accuracy. Key performance metrics, including accuracy, precision, recall, and F1 score, are presented to assess the ensemble model's robustness in real-world clinical applications. This research contributes to the advancement of medical image classification by showcasing the potential of ensemble methods in improving myocardial infarction detection accuracy.

***Index Terms* -** Myocardial infarction detection, Ensemble learning, Support Vector Machine (SVM), Random Forest, Convolutional Neural Network (CNN), AdaBoost, Electrocardiogram (ECG) images, Diagnostic accuracy, Feature extraction.

V. Introduction

Cardiovascular diseases, notably myocardial infarction (MI), persist as a predominant cause of global morbidity and mortality [1]. The imperative for timely MI detection to facilitate prompt intervention and enhance patient outcomes has underscored the significance of advanced medical image analysis techniques. Recent strides in this domain, particularly with electrocardiogram (ECG) images, hold promise for refining diagnostic capabilities. This paper addresses the formidable challenge of MI detection through an innovative ensemble-based strategy that amalgamates the distinct strengths of Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (CNN). SVM excels in navigating high-dimensional feature spaces [2], Random Forest demonstrates proficiency in ensemble learning [3], and CNN proves adept at hierarchical feature extraction from images [4].

While existing research frequently relies on individual models, the amalgamation of diverse models through ensemble methods has shown potential for significantly improving classification accuracy [4]. In this context, AdaBoost serves as the ensemble method, strategically integrating SVM, Random Forest, and CNN, thereby accentuating each classifier's unique strengths while mitigating their individual limitations.The research methodology, results, and discussions that resulted from applying this methodology are presented in the following sections of this paper. Additionally, conclusions are provided along with insights regarding future directions for research in the field of cardiovascular healthcare as well as potential practical applications.

I. ML and DL Model Integration

W. ML Models: SVM and Random Forest Classifier

The initial phase of myocardial infarction (MI) detection leverages two robust machine learning models: Support Vector Machine (SVM) and the Random Forest Classifier.

1. SVM (Support Vector Machine):

Support Vector Machine (SVM) is a robust machine learning algorithm designed for classification tasks, aiming to find an optimal hyperplane that separates different classes in the feature space[2]. In the context of myocardial infarction (MI) detection from electrocardiogram (ECG) images, SVM excels in discerning intricate patterns and capturing the underlying relationships within the data.SVM operates by mapping input data into a high-dimensional feature space, seeking a hyperplane that maximally separates different classes. It utilizes support vectors, which represent data points that are close to the decision boundary, to define this hyperplane[2].
The decision function in SVM is represented as:

$$(x) = sign\ (\textstyle\sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + b)$$

- $f(x)$ the decision function,
- x is the input feature vector,
- n is the number of support vectors,
- α_i and y_i are coefficients and labels of support vectors, $K(x, x_i)$ is the kernel function evaluating the similarity between x and x_i,
- b is the bias term.

2. Random Forest Classifier:

The Random Forest Classifier, a powerful ensemble learning method, is employed for the initial phase of myocardial infarction (MI) detection. In order to reduce overfitting and provide randomness, this model integrates predictions from several decision trees, each of which was trained on a distinct subset of the dataset.The algorithm involves random subset selection and bootstrap aggregating (bagging), creating diverse training samples for each tree. Decision trees, employing algorithms such as ID3, C4.5, or CART, utilize metrics like Gini impurity for data splitting, ultimately creating a tree structure[3].The ensemble's final prediction results from the aggregation of individual tree predictions, with the most commonly predicted class chosen for classification tasks. Random Forests offer benefits such as resilience to overfitting, handling of a large number of input features, and effective capture of complex data relationships[3]. Benefits from Random Forest are essential for MI detection. Because of its inherent resistance to overfitting, it may produce accurate predictions even when dealing with noisy or inconsistent ECG image data. Additionally, Random Forest offers feature importance metrics, which help find pertinent features that support MI detection.

A. DL Model: Convolutional Neural Network (CNN)

"Convolutional Neural Networks" (CNNs) are a group of DL models specifically designed for image classification and computer vision tasks[5]. However, CNNs can also be adapted to handle tabular or CSV (Comma-Separated Values) data, although the typical structure and operations may need to be modified.
A CNN consists of multiple layers, including "convolutional layers, pooling layers, and fully connected layers". The key feature of CNNs is their capability to Systematically learn and extract the features.
Formulas used in CNN:

- Convolution Operation: Think of this as a way for the computer to look at different parts of an image using special filters. These filters are like templates that help the computer recognize specific patterns, like edges or textures. By sliding these filters across the entire image, the computer can pick up different features in different locations.
- Activation Function: This is like a gatekeeper for the information flowing through the neural network. It decides which signals should pass through and which ones should be blocked. The most

common activation function, ReLU, [6]simply lets positive signals through unchanged, while blocking negative ones. This helps add complexity to the network's understanding of the data.

- Pooling Operation: Imagine you have a large picture and you want to focus on the most important parts while reducing the overall size. Pooling does just that. It looks at small sections [7]of the image and picks out the most important information, like the brightest spot in a small area. This aids in image simplification without sacrificing too many significant details.
- Fully Connected Layers: These function as the network's brain. Every neuron in one layer is linked to every other layer's neuron. This enables the network to comprehend intricate patterns and piece together various visual components. Activation functions are performed once more to introduce non-linearity after these connections, assisting the network in learning even more intricate associations between the characteristics.

B. Ensemble Models

AdaBoost Classifier:

AdaBoost, short for Adaptive Boosting, is an ensemble learning method used to improve the performance of weak classifiers and create a strong classifier. In the context of our myocardial infarction detection project, AdaBoost is applied with decision trees as base classifiers. Here's an overview of how AdaBoost works:

- Initialization: Assign equal weights to all training samples and initialize a weak learner on the training data. Training Weak Learners: Train the weak learner on the training set and evaluate its performance and calculate the error.
- Compute Classifier Weight: Compute the weight of the weak learner based on its error. Higher accuracy leads to a higher weight. Update Weights: Increase the weights of misclassified samples and decrease the weights of correctly classified samples.
- Repeat: Iterate the process by training a new weak learner. Weights guide the learning process, emphasizing misclassified samples.
- Combine Weak Learners: Combine the weak-learners with their respective weights to form a strong classifier.
- Final Prediction: For a new input, each weak learner votes based on its strength (weight). The combined votes determine the final ensemble prediction.

X. METHODOLOGY

The project involves detecting myocardial infarction (MI) using ECG images through a multi-step methodology. Initially, ECG images undergo preprocessing to extract relevant features. Subsequently, Support Vector Machine (SVM) and Random Forest classifiers are trained on these features to identify patterns indicative of MI. Additionally, Convolutional Neural Network (CNN) architecture is employed to automatically extract hierarchical features directly from ECG images for classification. To enhance overall accuracy, the predictions of SVM, Random Forest, and CNN are combined using the Adaboost algorithm.

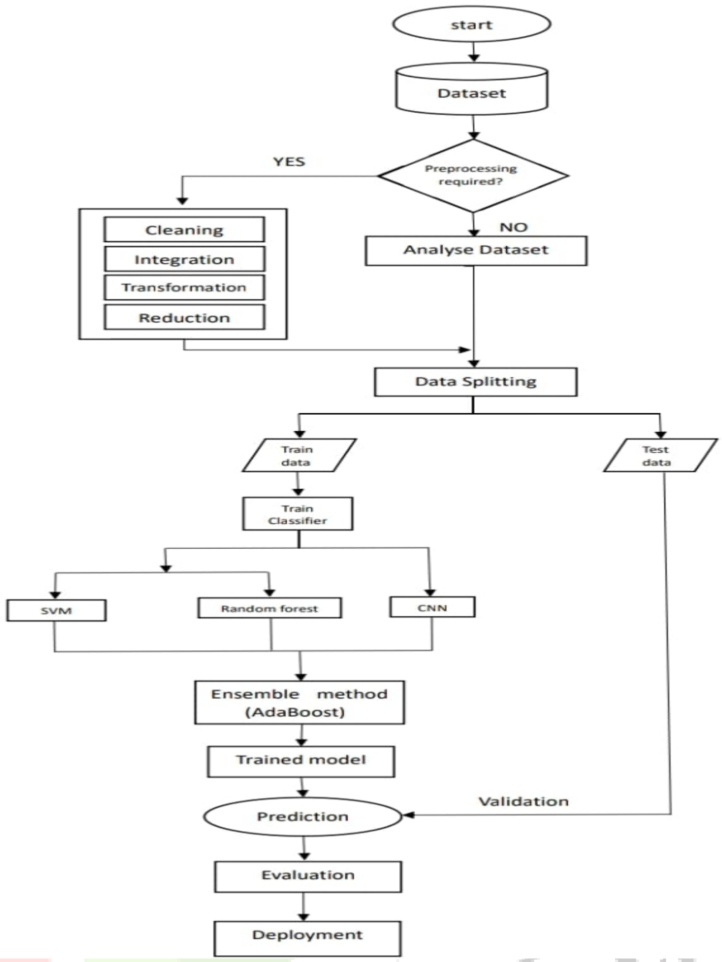

Fig.1: Architecture Diagram

A. Dataset selection

The dataset for training the ensemble-based myocardial infarction (MI) detection system is carefully curated from both Kaggle and Mendeley sources, encompassing a rich variety of electrocardiogram (ECG) images. The Kaggle dataset, comprising modified ECG images, is annotated to distinguish MI and non-MI cases, offering insights into diverse cardiac activity patterns. The Mendeley dataset contributes additional diversity in terms of patient populations, imaging conditions, and ECG variations. Rigorous curation involves the systematic removal of duplicates within each class. Further, data augmentation techniques, including rotations, scaling, and flipping, are employed to expand the dataset to 5000 images, ensuring a robust and diverse training set. This augmented dataset forms the foundation for training Support Vector Machines (SVM), Random Forest, and Convolutional Neural Network (CNN) models. The ensemble model, constructed by combining the strengths of these individual models using AdaBoost, is poised to exhibit enhanced predictive capabilities for accurate MI detection in diverse clinical scenarios.

B. Preprocessing

In the field of machine learning for myocardial infarction (MI) detection, a sophisticated image preprocessing pipeline has been developed, leveraging essential libraries such as os, numpy, and scikit-image [10]. At the heart of this pipeline is the meticulously crafted preprocess-image function, tailored to read and process electrocardiogram (ECG) images from designated folders, categorizing them as indicative of either MI or non-MI cases. Using a systematic file iteration loop, the function selectively filters images with ".png" or ".jpg" extensions, employing scikit-image's io.imread[10]for image reading. Crucially, the function ensures each image adheres to a standardized three-channel format, converting to RGB for grayscale images and retaining the first three channels for images exceeding this count. Subsequently, images are resized to consistent dimensions of (256, 256) using transform. resize[10]from scikit-image, ensuring uniformity for effective model training. The flattened images, along with corresponding labels, contribute to a cohesive dataset, further refined by the script's orchestration, defining paths to MI and non MI folders and consolidating processed images and labels into a unified dataset [9]. This meticulous approach, reinforced by the versatility of scikit-image and the foundational role of numpy for numerical operations[8], adeptly addresses challenges in image preprocessing, ensuring standardized data, and forming a robust foundation for subsequent machine learning endeavors in myocardial infarction detection.

C. Feature Extraction

Feature extraction becomes a crucial step for discerning relevant information in the context of myocardial infarction (MI) detection. This process involves extracting distinctive characteristics from the converted ECG images to facilitate the model's understanding of cardiac patterns within the original images.
Transformed Image Characteristics: The converted ECG images encapsulate key features related to the cardiac cycle, necessitating a focus on quantifying specific attributes. Feature extraction should emphasize capturing the shape and amplitude of ECG-like waveforms within these transformed images, which likely correspond to underlying cardiac activities within the original images.

- Pattern Recognition in ECG Images: Employ advanced image processing techniques to recognize and extract patterns reminiscent of typical ECG waveforms. This entails identifying distinct segments such as P-waves, QRS complexes, and T-waves within the transformed images, essentially mimicking the structure of conventional ECG signals [11]. Maintain a strategic distance from combining SI and CGS units, such as current in amperes and attractive field in oersteds. This frequently leads to disarray since conditions do not adjust dimensionally. If you must utilize blended units, clearly state the units for each amount that you utilize in an condition.

- Texture and Intensity Analysis: Perform a nuanced analysis of the texture and intensity patterns within the transformed ECG images. Features related to pixel intensities and spatial patterns can offer valuable insights into variations that may signify pathological conditions associated with MI [12].

- Spatial and Transient Characteristics: Given that the whole picture is changed over into an ECG-like representation, consider extricating highlights that capture the worldly advancement of ECG designs over distinctive locales of the picture. This all-encompassing approach gives a comprehensive see of the cardiac cycle and upgrades the model's capacity to perceive important data [13].

- Deep Learning-Based Features: Leverage the capabilities of deep learning, particularly convolutional neural networks (CNNs), for automatic feature extraction. CNNs can learn hierarchical features from the transformed ECG images, capturing intricate details that might be challenging to define manually. This approach empowers the model with a high-level understanding of the complex patterns within the converted images [14].

The significance of these feature extraction methods lies in their capacity to translate image-based information into actionable insights for MI detection. By distilling relevant characteristics, the model can more effectively discern normal and abnormal cardiac patterns, contributing to accurate and robust diagnostic outcomes.

D. Training, testing, Evaluating, Fine-tuning, and Deployment of a model:

- Preparing and Testing: Amid preparing, each person show (SVM, Irregular Timberland, CNN) is prepared utilizing labeled information. This includes nourishing the input information (highlights extricated from ECG pictures) into the models and altering their parameters to minimize the forecast blunder. SVM learns to partition diverse classes (e.g., myocardial dead tissue vs. non-myocardial dead tissue) by finding the ideal hyperplane. Arbitrary Woodland builds different choice trees based on irregular subsets of the information and combines their forecasts. CNN learns various leveled designs in ECG pictures through convolutional and pooling layers.[4]
- Evaluating: Metrics including accuracy, precision, recall, and F1-score are used to assess each model's performance separately. These measures offer valuable information into the models'

detection performance of myocardial infarction. The best-performing models can be chosen by evaluating their efficacy among models with the use of performance measures.[16]

- Fine-tuning: Fine-tuning involves adjusting the hyperparameters of the models to optimize their performance further. For example, in CNN, fine-tuning may involve changing the number of layers, adjusting learning rates, or trying different activation functions. Grid search or random search techniques can be used to systematically explore different hyperparameter combinations and identify the most effective ones.[17]
- Deployment: The models are prepared for use in practical applications once they have been trained, evaluated, and adjusted. The models are deployed by incorporating them into the myocardial infarction detection system. The deployed models anticipate outcomes, keep an eye on new ECG images, and notify medical staff of possible myocardial infarction patients.

IV. RESULTS AND DISCUSSION

The paper tells about the detection of Myocardial Infarction by training the dataset with the SVM model, Random Forest, and CNN model and finally, we are ensembling all three models using the Adaboost ensemble technique. The following are the results and discussions of the paper:

Accuracy: We have trained the SVM model, CNN model and Random forest model and we calculated performance measures like accuracy, F1-score, Precision, and Recall for each model.

The accuracy of the SVM model was almost 94%. The precision was 96% for class 0 (no myocardial infarction) and 92% for class 1 (myocardial infarction). Recall, which is a synonym for sensitivity, quantifies the percentage of real positive cases that the model accurately detected. Recall rates were 94% for class 0 and 95% for class 1. The harmonic mean of recall and precision yields the F1-score, which strikes a balance between the two measures. Class 0 had an F1 score of 95%, while class 1 had a score of 93%.

The Random Forest model achieved an accuracy of approximately 93%. Both classes (0 and 1) had high precision values, with class 0 having 93% precision and class 1 having 94% precision. Class 0 had a recall of 91%, and Class 1 had a recall of 97%. The F1 scores for both classes were also high, with class 0 having a score of 92% and class 1 having a score of 95%.

The accuracy of the Convolutional Neural Network (CNN) model was a remarkable 94%. Both classes showed strong precision rates; class 0 had a precision of 96%, while class 1 had a precision of 92%. Class 0 scored 94% and class 1 scored 95% in recall, respectively, demonstrating the model's ability to detect genuine positive cases. The class 0 and class 1 F1 scores, which represent the ratio of precision to recall, were equally remarkable, with 95% and 93%, respectively.

The AdaBoost ensemble method, incorporating CNN, SVM, and Random Forest models, delivered a notable accuracy of 94.3%. This ensemble exhibited remarkable precision rates across both classes, with class 0 demonstrating 96% precision and class 1 showcasing 94% precision. Additionally, class 0 and class 1 achieved recall rates of 95% and 96% respectively, highlighting the ensemble's capability to accurately identify true positive instances for both classes. The F1 scores further emphasized the ensemble's robust performance, with class 0 and class 1 achieving scores of 95% and 95% respectively. Despite the slight variation in accuracy compared to individual models, the AdaBoost ensemble effectively leveraged the strengths of diverse models to provide a highly accurate predictive framework for detecting myocardial infarction.

TABLE I We have compared the accuracy of the CNN model used in the base paper and the Adaboost model accuracy of our paper

Table 1: Compared Accuracy

SL	***Papers***	***Model***	***Accuracy***
1	Base Paper	Accuracy of CNN model (Base Paper)	96.30 %
2	Paper which we are working	Adaboost Model (CNN+SVM+Random Forest)	94.3%

V. CONCLUSION

The code implements a robust approach to classify electrocardiogram (ECG) images using various machine learning and deep learning techniques. It begins by preprocessing the images and encoding class labels, followed by training and evaluating Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (CNN) models individually. Each model is assessed for its accuracy and performance through classification reports. Furthermore, the code explores ensemble learning by combining SVM, Random Forest, and CNN features using AdaBoost, resulting in an integrated model with improved predictive capabilities. A Gradio interface is set up to enable users to upload ECG images and obtain real-time predictions from the trained models. Overall, this comprehensive approach offers valuable insights into the efficacy of different models for ECG image classification and provides a user-friendly interface for practical deployment.

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