Cardiovascular Disease Detection Using Deep Learning and ML Models on ECG Images

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***Abstract*— This paper introduces several Machine Learning Models and a CNN-based model for Cardio-Vascular disease prediction using ECG images, automating cardiovascular risk assessment. Our model preprocesses ECGs by converting them to grayscale, extracting 12 leads, and isolating the signal for training. The model classifies patients as infected, or normal, streamlining early heart disease detection.**

Keywords*— Electrocardiogram (ECG), Cardiovascular Disease Detection, Precision, Recall, F1-score, CNN, Signal Processing, Cardiovascular Detection

I. INTRODUCTION

Cardiovascular diseases remain a leading global health concern, necessitating efficient diagnostic tools. This research presents an automated heart disease detection system utilizing the ECG images dataset from Ch. Pervaiz Elahi Institute of Cardiology. Our approach employs Convolutional Neural Networks (CNNs) with comprehensive preprocessing techniques, including grayscale conversion, 12-lead extraction, and background removal. The model classifies patients into three categories: infected, or normal. This automated system offers a rapid, reliable solution for early heart disease detection, potentially reducing the burden on healthcare providers and improving diagnostic accuracy in clinical settings.

II. RELATED WORK

Many papers related to cardiovascular prediction focused on other features that included diet, age, gender, and many other dimensions, and then predicted for cardiovascular diseases based on these features. Our work is more on predicting diseases by providing the ECG chart to our model.

III. DATA

The dataset we're working with contains ECG images from both healthy individuals and those with heart problems. Before using these images in our system, each one goes through a critical preparation process - which is the most important phase of our project. We carefully clean, organize, and transform every ECG image to extract meaningful information in a format that our system can use effectively. This transformation process, which includes data preparation, cleaning, and feature extraction, ensures that we get the most accurate and useful information from each ECG scan for our analysis.

We convert the raw ECG image to Grayscale image using RGB2Grayscale function from Scikit-image library.

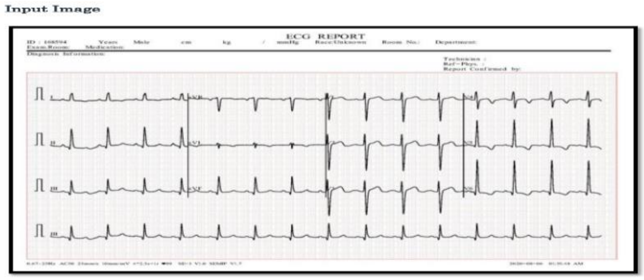

Figure 1.1 showing the converted grayscale image of ECG.

Data Cleaning & Feature Transformation:
After the conversion to Grayscale images, we prepare Leads (1-12) for further processing, each individual lead image is transformed by removing Gridlines, applying Gaussian filtering, and performing Thresholding to convert to binary image.

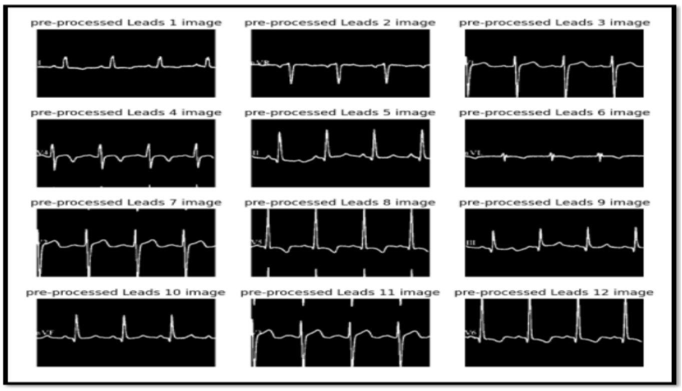

Figure 1.2 showing the converted processed image of ECG.

The transformed image is **traced** to extract only the signals from the image using the **contour technique**.

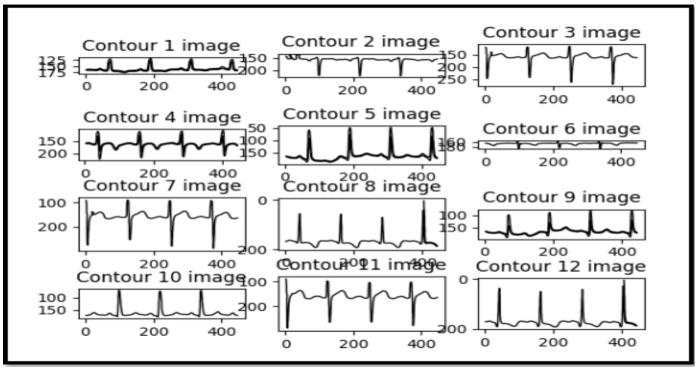

Figure 1.3 showing the contour images of ECG used for training.

IV. METHODOLOGY

a. Image Preprocessing:

- **Grayscale Conversion**: We converted ECG images to grayscale to reduce complexity while retaining essential heart activity features.
- **12-Lead Conversion**: We transformed the images into 12-lead representations, capturing the heart's electrical activity from multiple perspectives.
- **Background Removal**: We removed the background to isolate the heart signal and reduce noise, enhancing the model's focus on relevant features.
- **Signal Extraction**: We extracted the isolated heart signal from the processed images for training the model.

b. Machine Learning Models

- **Logistic Regression**:

Logistic regression classifies heart rate as "normal" or "abnormal" based on features extracted from ECG images. It outputs a probability score, helping identify health risks and supporting real-time monitoring in a simple, interpretable way.

Accuracy: 0.928

	Precision	Recall	f1-score	support
0	1.00	0.97	0.99	102
1	0.95	1.00	0.97	93
2	0.90	0.91	0.90	114
3	0.84	0.79	0.81	66

Table 1.1 showing metrics Precision, Recall, F1-Score for Logistic Regression.

For the Normal category, with a precision of 1.00, we correctly predicted true positives (TP) 100 times out of 100. For the Infected category, with a precision of 0.95, we correctly predicted true positives 95 times out of 100. False positives (FP) occur when a case is incorrectly classified as Infected, while false negatives (FN) occur when an infected case is missed. Precision reflects the accuracy of positive predictions, while recall and F1-score balance the model's ability to detect and classify cases correctly.

- **The K-Nearest Neighbors (KNN)**:

The K-Nearest Neighbors (KNN) algorithm classifies heart rate as "normal" or "abnormal" by comparing a person's ECG image data with similar past cases. It finds the "k" closest matches in the dataset and uses their labels for classification, supporting quick, interpretable health risk detection.

Accuracy: 0.936

	Precision	Recall	f1-score	support
0	0.98	1.00	0.99	102
1	1.00	1.00	1.00	93
2	0.88	0.93	0.91	114
3	0.86	0.76	0.81	66

Table 2.2 showing metrics Precision, Recall, F1-Score for KNN.

For the Normal category (precision = 0.98), we correctly predicted 98 out of 100 true positives. For Infected (precision = 1.00), we correctly predicted all true positives. For the third category (precision = 0.88), 88 out of 100 true positives were correctly predicted, and for the fourth (precision = 0.86), 86 out of 100. Precision reflects the accuracy of positive predictions, while recall and F1-score balance detection and classification performance.

- **The Support Vector Machine (SVM)**:

The Support Vector Machine (SVM) algorithm classifies heart rate as "normal" or "abnormal" by finding an optimal boundary that separates ECG features. It maximizes the margin between classes, helping detect health risks accurately and reliably, especially when data is complex or overlapping.

Accuracy: 0.9616

Table 3.3 showing metrics Precision, Recall, F1-Score for SVM.

	Precision	Recall	f1-score	support
0	0.98	1.00	0.99	120
1	1.00	1.00	1.00	119
2	0.93	0.96	0.95	145
3	0.92	0.86	0.89	85

For the Normal category (precision = 0.98), we correctly predicted 98 out of 100 true positives. For Infected (precision = 1.00), all true positives were correctly predicted. For the third category (precision = 0.93), 93 out of 100 true positives were correctly predicted, and for the fourth (precision = 0.92), 92 out of 100. Precision indicates the accuracy of positive predictions, while recall and F1-score balance detection and classification performance.

c. Deep Learning Model (CNN):

- **Convolutional Layers**: We used convolutional layers to automatically extract important features from the preprocessed ECG images.
- **Max-Pooling Layers**: We applied max-pooling layers to reduce dimensionality and retain critical information.
- **Fully Connected Layers**: We flattened the feature maps and used fully connected layers to classify the images into "Normal" or "Abnormal" categories.
- **Compilation**: We compiled the CNN model with the Adam optimizer (learning rate = 0.001) and binary cross-entropy loss for binary classification.
- **Training**: We trained the model on the preprocessed ECG images for a specified number of epochs (e.g., 10 epochs) using a batch size of 32.After finishing the analysis, the model returns the results back to the user based on the findings.
- **Model Evaluation**: We evaluated the model's accuracy on the validation set to assess its performance in classifying ECG images.

V. EXPERIMENTS AND RESULTS

Image conversion techniques such as RGB to grayscale conversion, denoising, Gaussian filtering, and thresholding were implemented to extract signals without the grid lines.

The CNN model achieved 98% accuracy on the training set, indicating strong learning from the ECG images. On the validation set, it reached 92% accuracy, showing good generalization to unseen data. These results demonstrate the model's effectiveness in classifying ECG images for heart disease detection.

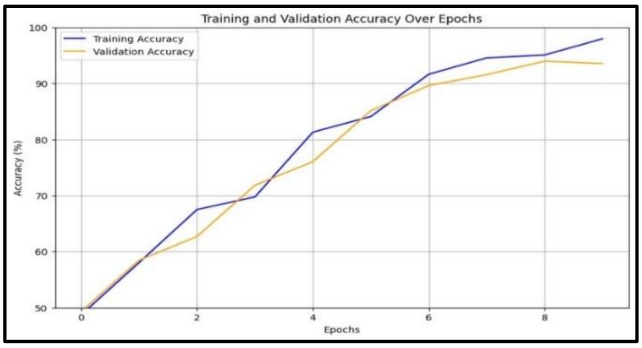

Figure 1.4 showing the metrics of training and validation accuracy.

VI. APPLICATIONS

Our work has significant applications in healthcare, particularly in the early detection of heart diseases. By automating the analysis of ECG images using Convolutional Neural Networks (CNNs), we provide a fast, accurate, and reliable method for diagnosing heart conditions. This system can help healthcare professionals identify patients at risk of heart disease or those with existing conditions, enabling faster decision-making and reducing the reliance on manual ECG interpretation. It can also be integrated into telemedicine platforms, offering accessible heart disease screening in remote areas.

VII. CONCLUSION

The empirical results demonstrate that we can generate faster and more accurate predictions for heart patients by applying the predictive model to the ECG images of new patients. The model shows promising potential in improving the efficiency of heart disease detection. This study can also be extended to include the detection of multiple heart diseases, provided the feature extraction from images is done optimally. Additionally, further model improvements could lead to higher accuracy, enhancing its applicability in clinical settings.

ACKNOWLEDGEMENT:

We gratefully acknowledge Prof. Animesh Chaturvedi for helping us throughout.

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ADDITIONAL RESOURCES:

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