

A Framework for Predicting Analytics of Cardiovascular Disease using Convolutional Neural Networks (CNN)

Thiyagu T¹, M. Azhagiri², Tamilselvan T³, Govinda Rajulu. G⁴, Ganeshan R⁵ and Pragadeeswaran Sundaresan⁶
^{1,3-6}School of Computing, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India

Email: thiyagu.57@gmail.com, tamilselvan.akash@gmail.com, rajulug7@gmail.com, ganeshramasamy111@gmail.com, pragadeesresearch@gmail.com

²Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, India
Email: azhagiri1687@gmail.com

Abstract— To use deep learning methods—specifically, convolutional neural networks, or CNNs—to find anomalies in sizable medical data sets, enabling precise cardiovascular health evaluation and diagnosis. To enhance heart disease detection, risk assessment, and management, a strong model that recognizes intricate patterns and temporal correlations in cardiovascular data is being developed. CNNs process ECG images one after the other and categorize them according to heart rhythm. Data gathering, preprocessing, model building, training, and evaluation are all included in the workflow. Beyond conventional techniques, the trained model demonstrates promise for automated ECG analysis. To assess the model's performance and pinpoint areas in need of development, we employ confusion matrices, accuracy curves, and loss curves. Deep learning's potential to enhance automated analysis and cardiac diagnostics is demonstrated by the model's ability to classify ECG images. Use real-time ECG analysis to validate the model for clinical decision support in cardiac care in order to increase its generalizability and explain ability. The results highlight the need for innovation in cardiac care and open the door for precision medicine and AI-driven healthcare solutions. Through the classification and analysis of ECG images, deep learning enhances the accuracy of cardiovascular health diagnostics and patient outcomes.

Index Terms— Cardiovascular Disease, Convolutional Neural Network (CNN), Predictive Analytics, Deep Learning, ECG Analysis.

I. INTRODUCTION

This study delves into the pressing global issue of cardiovascular diseases (CVDs), which continue to pose significant challenges in healthcare due to their high rates of morbidity and mortality. Addressing these challenges demands advanced diagnostic approaches capable of accurately identifying and assessing cardiovascular abnormalities. Following the emergence of deep learning techniques has offered a promising avenue for revolutionizing healthcare by providing powerful tools for pattern recognition and data analysis. The principal focus of this reading is to harness the potential of deep learning methodologies to enhance the early detection and assessment of CVDs, aiming to increase patient results and healthcare practices.

The integration of convolutional neural networks (CNNs) [10] stands as a pivotal advancement in cardiovascular health assessment. Electrocardiograms, or ECGs, are a cornerstone of diagnosing and monitoring heart health. This painless test measures the electrical activity of your heart, revealing abnormalities in rhythm or damage to the heart muscle.

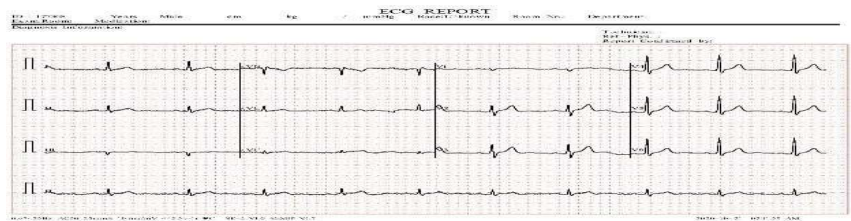


Figure 1: Normal ECG

By leveraging the capabilities of deep learning models, this research endeavors to transcend traditional diagnostic methods and deliver more precise and timely identification of cardiovascular abnormalities. This proactive approach facilitates earlier intervention and treatment strategies, ultimately leading to improved patient outcomes. Furthermore, the learning seeks to deepen our appreciative of how deep learning techniques can be effectively applied in cardiovascular health assessment, uncovering valuable insights for healthcare practitioners and decision-makers. The overarching goal of this research is to enhance diagnostic precision, refine risk prediction, and optimize patient outcomes in the realm of cardiovascular diseases. By contributing to the ongoing evolution and advancement of healthcare practices, this study aims to make significant strides in tackling the global burden of CVDs and improving the quality of care for affected individuals.

II. RELATED WORKS

Research in ECG image classification encompasses a wide range of investigations into the effectiveness of different deep learning architectures, particularly focusing on convolutional neural networks (CNNs) and their combinations. Notable studies conducted by [1, 2] have contributed significantly to this field by comparing the performance of these architectures in categorizing ECG images into distinct arrhythmia classes. Furthermore, researchers have extended their focus to the detailed classification of specific ECG abnormalities, with a particular emphasis on detecting Myocardial Infarction (MI) using deep learning methods. [3] The exploration of deep learning approaches for arrhythmia detection remains a crucial aspect of this domain, with studies such as those conducted by [5] examining various ECG image representations suitable for this task. In response to the "black box" nature of deep learning models, recent investigations have concentrated on Explainable AI (XAI) techniques tailored specifically for ECG classification models. Research conducted by [6] and similar studies have explored methodologies aimed at elucidating the decision-making processes of these models, thereby enhancing their interpretability and trustworthiness in clinical contexts. In emerging applications in mobile health (mHealth) have underscored the potential of deep learning for mobile ECG analysis, despite the challenges associated with deploying models on devices with limited computational resources. Studies conducted by [7] and related research endeavors have focused on optimizing deep learning models for deployment on mobile platforms. Simultaneously, they have explored real-time health monitoring capabilities for the early detection of heart abnormalities, as exemplified by research conducted by [8].

III. CARDIOVASCULAR DISEASE USING CONVOLUTIONAL NEURAL NETWORK (CNN)

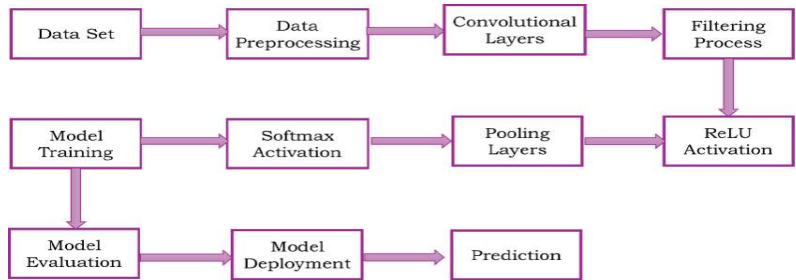


Figure 2: Diagram for Prediction of cardiovascular disease using CNN

Cardiovascular Disease Dataset (Cleveland Clinic) consists of the Features Patient's age, Sex: The patient's gender (either male or female), Type of chest pain (CP): Characteristics of the felt chest pain, Trestbps: Blood pressure at rest (in mm Hg), Chol: The amount of serum cholesterol (mg/dl), Fasting blood sugar, or FBS: Blood sugar level when fasting (> 120 mg/dl = 1; otherwise = 0), Restecg: Electrocardiogram findings at rest, Thalach: Heart rate attained maximum, Exang: Angina brought on by exercise (1 = yes; 0 = no), Oldpeak: Exercise-induced ST depression in comparison to rest, Slope: The peak exercise's slope ST section, Ca: Fluoroscopy-colored main vessels (0–3) in number, Thal: Thalassemia (1 = fixed defect; 2 = normal; 3 = reversible defect), Num: Heart disease diagnosis (0–4), For the analysis of many factors influencing cardiovascular health and illness risk, this dataset is essential.

This architecture provides a robust framework for developing and deploying deep learning models for cardiovascular disease detection. The architecture for detecting cardiovascular diseases using deep learning methods consists of several interconnected stages. Initially, data collection involves gathering various healthcare data sources, including electronic records (EHR), wearable sensors, and medical imaging. Following this, data preprocessing steps, including cleaning, normalization, and feature extraction, prepare the data for analysis. Feature extraction involves extracting relevant features, employing techniques like signal processing and image analysis tailored to different data types..

Data Preprocessing: The ECG images and their corresponding labels from the dataset folders are loaded. Next, we downsize the pictures to a specific size to ensure consistency across the collection [15]. We transform the pixel values from the photos into NumPy arrays and normalize them to a range of 0 to 1, thereby enhancing the efficiency of training. This normalizing phase puts the data on a consistent scale, which enhances model performance.

Convolutional Layers: The model is built on convolutional layers that use ReLU activation functions to successfully pull-out features from the ECG picture data. These layers employ filters to find patterns and regional traits that are essential for categorization. The design employs activation='relu' to introduce non-linearity, and incorporates Conv2D with predetermined filters and kernel size.

ReLU: Deep learning architectures frequently employ the Rectified Linear Unit, (ReLU), as a non-linear activation function, particularly in convolutional neural networks. ReLU gives the model the ability to learn intricate relationships between input data and intended outputs by incorporating nonlinearity

ReLU function is: $(x) = \max(0, x)$.

Eq (1)

The model is built on convolutional layers that use ReLU activation functions to successfully pull-out features from the ECG picture data. These layers employ filters to find patterns and regional traits that are essential for categorization. The design employs activation='relu' to introduce non-linearity, and incorporates Conv2D with predetermined filters and kernel size. We utilize MaxPooling2D to minimize computational strain, preserve essential features, and minimize spatial dimensions. We repeat these layers as necessary (usually three to four times) to gradually extract more intricate information from the ECG images.

cardiovascular disease Model using CNN

```
buildModel()INITIALIZE model as Sequential
model.ADD Conv2D with 32 filters, (3, 3) kernel, activation='relu', input_shape=(height, width, channels)
model.ADD MaxPooling2D with (2, 2) pool size,
model.ADD Conv2D with 64 filters, (3, 3) kernel, activation='relu'
model.ADD MaxPooling2D with (2, 2) pool size
model.ADD Dropout with rate=0.5, model.ADD Flatten(), Add Dense Layers
model.ADD Dense with 128 units, activation='relu', model.ADD Dropout with rate=0.5
model.ADD Dense with num_classes units, activation='softmax' // for multi-class classification
RETURN model
```

Fig 3.

This layer transforms the 2D output from the preceding layers into a 1D array, preparing it for input into fully connected layers. This layer is dense, combining the characteristics discovered by the convolutional layers using a ReLU activation function. This dense layer provides the final prediction based on the gathered characteristics and utilizes a sigmoid activation function for binary classification. Computational Efficiency: ReLU stands out for its computational efficiency due to its simpler mathematical operation compared to activation functions like sigmoid or tanh. This can be beneficial for training large CNN models used for ECG image classification.

Softmax Activation: The dense layer of the model utilizes the softmax activation function to generate probability scores for each ECG classification. This function transforms the raw output logs into a probability distribution, ensuring that the sum of all output probabilities equals one.

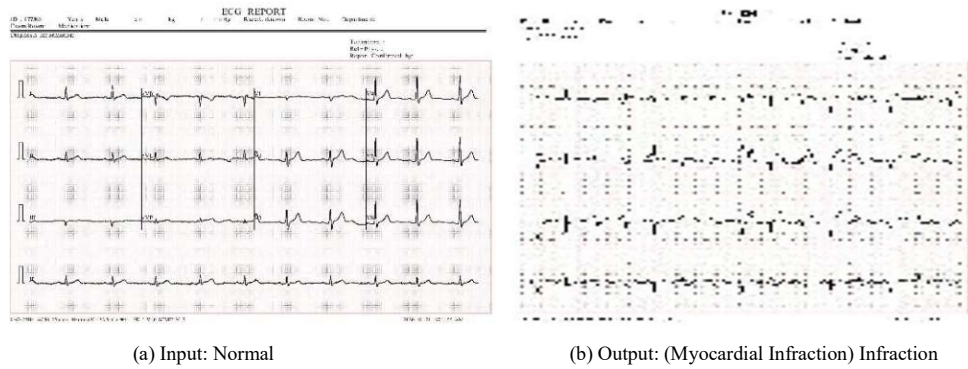


Figure 4 (A) Normal ECG (B) Myocardial

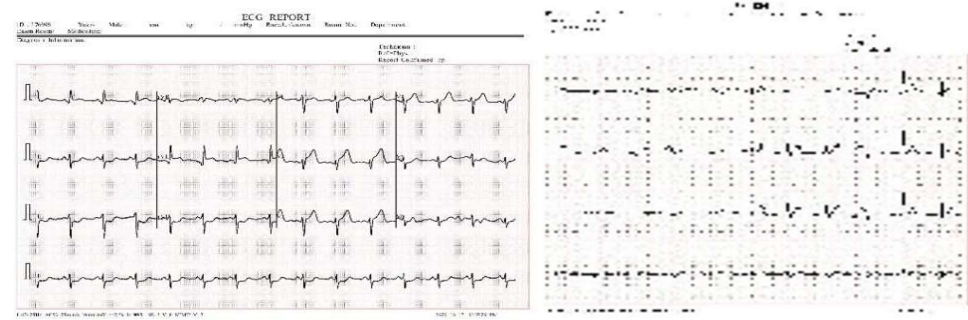


Figure 5: (A) Myocardial Infarction (B) Normal Heart Beat

The Adam optimizer is a prominent deep learning model optimization algorithm, including CNNs. Adam estimates first and second gradient moments (mean and uncentered variance) to calculate parameter learning rates. Adam smooths updates with momentum. It builds a gradient moving average to accelerate updates in the right direction and suppress oscillations. Adam adds bias correction components to the first moment (mean) and second moment (variance) estimations to counterbalance the initial bias toward zero. $m_t=0$ (First moment), $v_t=0$ (Second moment), $t=0$ (Time step)

For each parameter θ :

Compute gradients: $g_t = \nabla J(\theta_t)$ Eq(2)

Increment time step: $t=t+1$ Eq(3)

Update biased first moment estimate: $m_t = \beta_1 \cdot m_{t-1} + (1-\beta_1) \cdot g_t$ Eq(4)

Update biased second moment estimate: $v_t = \beta_2 \cdot v_{t-1} + (1-\beta_2) \cdot g_t^2$ Eq(5)

Compute bias-corrected first moment $\hat{m}_t = \frac{m_t}{1-\beta_1^t}$ Eq(6)

Compute bias-corrected second moment: $\hat{v}_t = \frac{v_t}{1-\beta_2^t}$ Eq(7)

Update Parameter: $\theta = \theta - \frac{\alpha}{\sqrt{\hat{v}_t} + \epsilon} \cdot \hat{m}_t$ Eq(8)

Where: α = learning rate, β_1 = decay rate for the first moment, β_2 = decay rate for the second moment
 ϵ = small constant to prevent division by zero

Fig 6

Model Training: The dataset is split into training and testing subgroups following preprocessing. Using the training data, the model gains the ability to optimize its weights and biases. By measuring the difference between the expected and actual class labels, the loss function such as categorical cross-entropy is minimized during this optimization phase.

The loss function is a critical component in training machine learning models, as it quantifies the difference between the predicted outputs and the actual targets. People commonly use the categorical cross-entropy loss for multi-class classification problems like ECG classification.

$$Loss = -\sum_{i=1}^C y_i \log (P_i) \quad \text{Eq (9)}$$

where the number of classes is C. The true label, denoted by y_i , is 1 for the correct class and 0 for others. P_i is the softmax output's predicted probability for class I.

ModelCompilation: The appropriate loss function, typically categorical cross-entropy for multi-class classification problems, is specified in order to evaluate the model's performance. This function calculates the degree to which the actual class labels and the predicted probabilities match. The model's performance during training and validation can be tracked with metrics like accuracy. Performance metrics such as accuracy and area under the ROC curve (AUC) are evaluated during model evaluation. After a successful evaluation, the models are put into use in real-world settings, connected to medical systems, and their performance is regularly assessed. Model adaptation and accuracy maintenance over time are ensured by periodic retraining with updated data. This architecture offers a methodical way to use deep learning techniques to identify cardiovascular conditions, enabling prompt diagnosis and treatment to enhance patient outcomes.

IV. RESULT

Comparing the computational time and resources required by the proposed solution with those of other existing solutions is essential for practical implementation, particularly in actual medical applications where productivity is critical. Understanding the trade-offs between model production and computational complexity can inform managerial procedures and monitor the progress of more efficient and scalable solutions. Moreover, discussing the ethical implications of using AI for medical diagnosis, including privacy, data security, and potential biases, is essential for responsible development and deployment. By addressing these ethical considerations, we can ensure that AI-based solutions uphold patient rights and adhere to ethical standards in healthcare.

In the realm of lung disease classification, the proposed study denotes a important progress in the application of deep learning methodologies. By presenting a comprehensive deep learning scheme and leveraging a novel hybrid deep neural network, the research aims to overcome existing limitations in lung disease diagnosis based on medical images. The amalgamation of pre-processing techniques further enhances the success of the proposed deep learning scheme by optimizing input data quality. This meticulous attention to data quality aligns with the broader objective of achieving higher accuracy and reliability in identifying and classifying lung diseases from medical images. The confusion matrix is a vital tool in estimating the performance of a grouping model, including those used in the detection of cardiovascular diseases through deep learning methods

The accuracy and loss graph are a graphic assessment of a prototype's performance as a deep learning model over the course of training and validation. It serves as a crucial tool for understanding how well the model is learning from the data and successful its predictive capabilities. In the context of detecting cardiovascular diseases using deep learning methods, the accuracy and loss graph provides evaluation of the model's effectiveness in correctly predicting class labels of cardiovascular abnormalities and its convergence towards optimal performance.

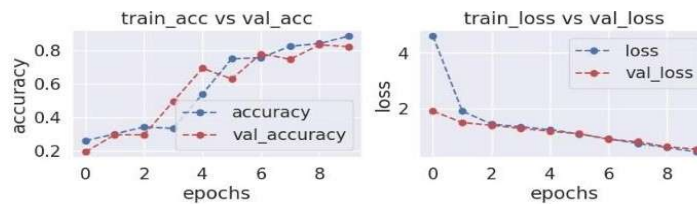


Figure 5: Graphical Representation of System Performance

A classification report offers a detailed evaluation of a classification model's performance, outlining key metrics for each class within the dataset. In the context of detecting cardiovascular diseases using deep learning methods, a classification report would offer insights into how well the model classifies different rdiovascular conditions.

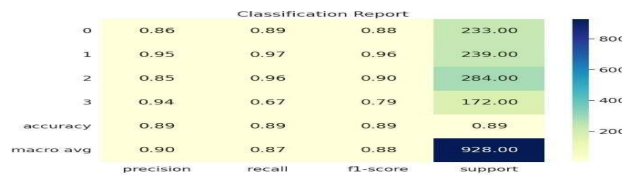


Figure 6: Graphical Representation for Classification

V. CONCLUSION

By predicting cardiovascular health from ECG images. The suggested system uses huge medical datasets to discover irregularities, improve early detection, and quantify cardiovascular disease risk. The model architecture's numerous convolutional and dense layers efficiently extract complex ECG characteristics. ReLU activation functions create non-linearity, allowing the model to learn complex patterns. A clear probabilistic output from the softmax activation function in the last layer aids multi-class categorization. Rigid data preprocessing and effective model training, using categorical cross-entropy as the loss function and the Adam optimizer, optimize performance and classification accuracy. Deep learning improves automated ECG analysis, promising cardiovascular diagnostics applications. This research should increase model generalizability and explain ability and provide real-time analysis. To confirm the model's reliability in healthcare professional decision-support systems. This system establishes the framework for precision medicine and AI-driven healthcare solutions, demonstrating cardiovascular care's potential for continual innovation. The framework uses deep learning to improve diagnosis and patient outcomes, advancing cardiovascular health technology.

REFERENCES

- [1] Yang, Y. Yu, J. Xu, H. Shu, H. Liu, Y. Wu, et al., "Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan China: A single- centered retrospective observational study", *Lancet Respiratory Med.*, vol. 8, no. 5, pp. 475-481, 2020.
- [2] J. Zhang, Y. Xie, G. Pang, Z. Liao, J. Verjans, W. Li, et al., "Viral pneumonia screening on chest X-ray images using confidence-aware anomaly detection", *arXiv:2003.12338*, 2020.
- [3] N. Ghassemi, A. Shoeibi, M. Khodatars, J. Heras, A. Rahimi, A. Zare, et al., "Automatic diagnosis of COVID- 19 from CT images using CycleGAN and transfer learning", *arXiv:2104.11949*, 2021.
- [4] S. R. Nayak, D. R. Nayak, U. Sinha, V. Arora and R. B. Pachori, "Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: A comprehensive study", *Biomed. Signal Process. Control*, vol. 64, Feb. 2021.
- [5] A. Iqbal, M. Usman and Z. Ahmed, "An efficient deep learning-based framework for tuberculosis detection using chest X-ray images", *Tuberculosis*, vol. 136, Sep. 2022.
- [6] M. E. Sahin, "Deep learning-based approach for detecting COVID-19 in chest X-rays", *Biomed. Signal Process. Control*, vol. 78, Sep. 2022.
- [7] A. L. Bui, T. B. Horwich, and G. C. Fonarow, "Epidemiology and risk profile of heart failure," *Nature Rev. Cardiol.*, vol. 8, no. 1, p. 30, 2011.
- [8] M. Durairaj and N. Ramasamy, "A comparison of the perceptive approaches for preprocessing the data set for predicting fertility success rate," *Int. J. Control Theory Appl.*, vol. 9, no. 27, pp. 255–260, 2016.
- [9] L. A. Allen, L. W. Stevenson, K. L. Grady, N. E. Goldstein, D. D. Matlock, R. M. Arnold, N. R. Cook, G. M. Felker, G. S. Francis, P. J. Hauptman, E. P. Havranek, H. M. Krumholz, D. Mancini, B. Riegel, and J. A. Spertus, "Decision making in advanced heart failure: A scientific statement from the American heart association," *Circulation*, vol. 125, no. 15, pp. 1928–1952, 2012.
- [10] S. Ghwanmeh, A. Mohammad, and A. Al-Ibrahim, "Innovative artificial neural networks-based decision support system for heart diseases diagnosis," *J. Intell. Learn. Syst. Appl.*, vol. 5, no. 3, 2013, Art. no. 35396.
- [11] Q. K. Al-Shayea, "Artificial neural networks in medical diagnosis," *Int. J. Comput. Sci. Issues*, vol. 8, no. 2, pp. 150–154, 2011.
- [12] J. Lopez-Sendon, "The heart failure epidemic," *Medicographia*, vol. 33, no. 4, pp. 363–369, 2011.
- [13] P. A. Heidenreich, J. G. Trogon, O. A. Khavjou, J. Butler, K. Dracup, M. D. Ezekowitz, E. A. Finkelstein, Y. Hong, S. C. Johnston, A. Khera, D. M. Lloyd-Jones, S. A. Nelson, G. Nichol, D. Orenstein, P. W. F. Wilson, and Y. J. Woo, "Forecasting the future of cardiovascular disease in the united states: A policy statement from the American heart association," *Circulation*, vol. 123, no. 8, pp. 933–944, 2011.