



RESEARCH ARTICLE

Integrating clinical and ECG data for heart disease prediction: A hybrid deep learning approach based on two modalities with particle swarm optimization

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Abstract

Cardiovascular diseases (CVDs) remain a leading global health concern, emphasizing the need for accurate and early diagnostic systems. This study introduces a hybrid deep learning model that leverages dual-modality data by integrating clinical tabular data and ECG images for heart disease prediction. Both datasets comprising clinical features and corresponding ECG images of the same individuals and these datasets are real-time datasets. Feature extraction from ECG images is conducted using a fine-tuned EfficientNetB0 convolutional neural network, while features from the clinical dataset are extracted using a Dense Neural Network (DNN). To enhance the model's predictive performance and reduce dimensionality, Particle Swarm Optimization (PSO) is employed to select the most relevant features from the combined feature space. The proposed dual-modality model uses a fine-tuned DNN classifier, incorporating dense and dropout layers to prevent overfitting and improve generalizability. Extensive pre-processing techniques, including image augmentation and standardization of clinical features, were applied to ensure data quality. The model achieved an accuracy of 86.13%, precision of 87%, recall of 89%, and an F1-score of 88%, significantly outperforming traditional single-modality models. Additionally, it demonstrated strong discriminative capability with a ROC AUC of 0.93. These results highlight the effectiveness of combining diverse data types and optimizing feature selection using IPSO to support clinical decision-making in heart disease diagnosis.

Keywords: Cardiovascular diseases, Electrocardiogram, EfficientNetB0, Dense neural network, Dual-Modality model, Heart diseases, Coronary Heart Disease, Single-Modality models, Particle Swarm Optimization.

Introduction

Cardiovascular diseases (CVDs) are a major global health issue, causing millions of deaths annually. Their prevalence

is rising due to factors like sedentary lifestyles, poor diets, smoking, alcohol consumption, and stress. Age, elevated cholesterol, high blood pressure, obesity, diabetes, gender, and body mass index (BMI) are also some of the major challenges to CVDs (Az-Zahra, 2024). CVDs, including heart attacks, strokes, peripheral arterial disease, coronary artery disease (CAD), and arrhythmias, affect people of all ages (World Health Organization, 2021; Rahim et al., 2021). Heart attacks occur when blood flow to the heart is blocked, while CAD is caused by plaque builds up in arteries. Strokes result from blood flow disruptions to the brain, either through clots (ischemic) or ruptured blood vessels (hemorrhagic) (Mondal et al., 2024). Arrhythmias, such as tachycardia and atrial fibrillation, can lead to dizziness, fainting, and stroke. Early diagnosis is crucial to prevent severe complications and fatalities.

17.9 million deaths happened in 2019 due to CVDs, in which 32% of global fatalities were most notably from heart attacks and strokes (World Health Organization, 2021; Mondal et al., 2024). The number of CVD-related deaths has surged from 12.1 million in 1990 to 20.5 million in 2021 (World Heart Federation, 2023), with a staggering 12.5% rise

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How to cite this article: Boya, B., Devaraju, P. (2025). Integrating clinical and ECG data for heart disease prediction: A hybrid deep learning approach based on two modalities with particle swarm optimization. *The Scientific Temper*, **16**(5):4232-4241.

Doi: 10.58414/SCIENTIFICTEMPER.2025.16.5.08

Source of support: Nil

Conflict of interest: None.

in heart attack deaths in India alone in 2022 (India Today, 2023). The WHO projects 23.6 million CVD deaths by 2030 (Abdellatif et al., 2022). These alarming figures highlight the urgent need for early detection, advanced diagnostics, and preventive strategies to reduce mortality and alleviate pressure on healthcare systems. Traditional methods, relying on clinical risk factors to predict CVDs, often miss crucial details in cardiovascular health. The electrocardiogram (ECG) is a fundamental, non-invasive diagnostic tool that is widely used in the detection and management of heart diseases. ECG can record the electrical activity of the heart and it provides critical insights into cardiac function, helping to identify conditions such as arrhythmias, myocardial infarction, and structural abnormalities at an early stage. Recent advancements in machine learning and deep learning techniques using ECG images offer a more accurate and efficient approach for detecting heart conditions (Bandari & Jhitri, 2023).

Review Literature

Here, the literature types are listed with the consideration of the deep learning and machine learning based heart stroke prediction models. Certain studies focus solely on standalone machine learning and deep learning models, while others explore ensemble-based machine learning and deep learning models. Many authors have used a structured clinical data or unstructured data to predict heart diseases but not use integrated structured and unstructured data.

Subhash Mondal et al. (2024) was crafted a robust two-stage stacking ensemble prediction model for heart disease prediction utilizing Random Forest, Extreme Gradient Boost, and Decision Tree algorithms. The GridSearchCV and RandomizedSearchCV techniques were employed to fine-tune the parameters of each model for optimal performance. The stacking model achieved an impressive ROC-AUC score of 0.96, a recall rate of 0.98, and an outstanding accuracy level of 96%. The research study suggests the possibility of further enhancing this work by integrating feature selection algorithms and applying them to reduced features in order to uncover new insights.

Abdallah Abdellatif et al. (2022) was introduced an ensemble model (Inf-FSS+BO+IWRF) in order to predict the incidence of CVD and the survival of patients on two distinct datasets. The proposed model outperforms other machine learning models of achieving up to 98.3% accuracy, 98.6 % precision, 97.2% recall, and 99.1% f1-score for the Statlog dataset and 97.2 % accuracy, 94.4% precision, 94.3% recall, and 98.2% f1-score for HD clinical dataset.

Abdulwahab Ali Almazroi et al. (2022) were proposed a model to accurately identify cardiac diseases using a dense neural network in a deep learning model, which achieved an accuracy of 83%. Their proposed model performed a significant improvement in accuracy, sensitivity, and specificity when compared to other models. Future work

was left to enhance the proposed model by incorporating images data from patients with clinical heart disease data. In addition, CNN will be utilized on the image data to accurately diagnose heart disease. Furthermore, the CNN model can also be utilize to test on combined structured and unstructured data.

Aqsa Rahim et al. (2021) were proposed an algorithm for estimating cardiovascular disorders with 95.5%, 98.0%, and 99.1% of three different datasets by using the MaLCaDD framework that consists of the KNN and the Logistic Regression classifiers. The framework uses the mean replacement technique to address missing values, SMOTE to address data imbalance, and feature importance to select features. Finally, an ensemble of LR, KNN classifiers is proposed for prediction with higher accuracy.

Minhaz Uddin Emon et al. (2020) conducted research utilized a set of ten classifiers to evaluate how well they can determine the likelihood of stroke in individuals. They introduced a weighted voting classifier that takes into account clinical data attributes such as sex, age, blood pressure issues, heart conditions, average glucose levels, and others to forecast stroke occurrences. This weighted voting approach achieved an impressive accuracy rate of 97%. They suggested that future investigations could integrate deep learning-based imaging techniques, such as brain CT scans and MRIs, alongside the current model to enhance performance metrics.

Prashant Kunwar et al. (2022), introduced layered ensemble CNN architecture for stroke diagnosis utilizing patient ECG data. This model achieves impressive results with an accuracy of 99.7%, recall of 99.69%, precision of 99.71% and an F1-score of 99.67%. The suggested model is suitable for implementation on larger datasets, encompassing both binary and multi-class scenarios in future research.

Mingxing Tan et al. (2019) conducted a systematic study on ConvNet scaling and found that the width, depth, and resolution of the network must be carefully balanced. They proposed a simple and efficient compound scaling technique that allows the underlying convolutional network to easily adapt to all target resource constraints in a more principled manner.

Prashant Kumar Shrivastava et al. (2022) proposed a novel hybrid model based on deep learning techniques to predict the presence or absence of heart disease in a person using CNN and Bi-LSTM. They used data pre-processing methods to address the issues of missing data and imbalanced data in the Cleveland UCI Cardiology dataset. The outcomes from their model revealed a remarkable accuracy of 96.66%, a recall of 96.66%, precision reaching 96.84%, and F1-score.

Methodology

Machine learning and Deep learning are part of artificial intelligence (AI) and which are now widely used in the healthcare and medical fields to early predict diseases.

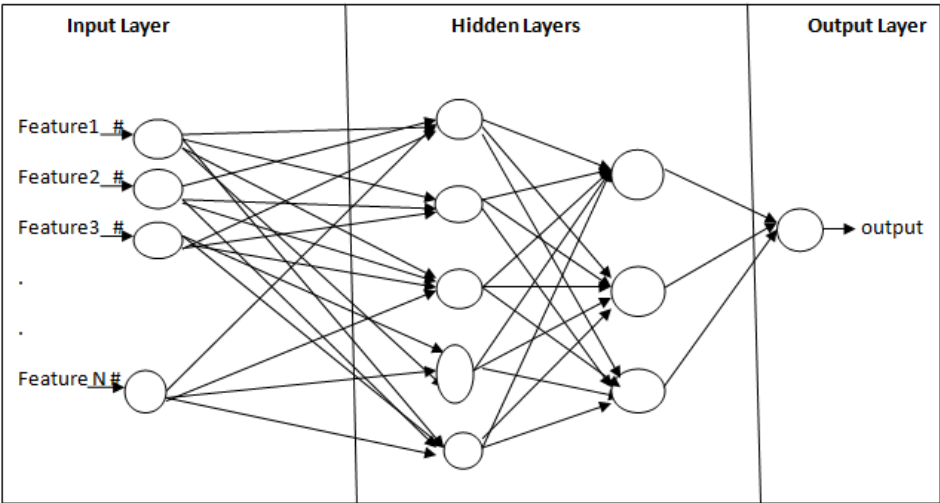


Figure 2: Architecture of used Dense Neural Network (DNN)

physiological variables as age, sex information. This dataset consists of 15 attributes: 14 independent features and one target variable indicating heart risk, with 1190 instances, including 272 duplicates. A detailed description of the dataset’s features is provided in Table 1.

ECG Image Data

This ECG dataset is also collected from Government General Hospital, data of from year 2019-2024 (Govt. General Hospital, Cardio Department, n.d.,2024) of the same individuals, which includes 1190 images in that 629 normal ECG images and 561 abnormal images.

Pre-processing of Datasets

An essential step in ML or DL models is data pre-processing, which includes feature selection, data cleaning, normalization, and standardization. Several data pre-processing techniques (Ashrafuzzaman, Saha, & Nur, 2022) have been appropriately applied to the datasets utilized in our research.

Clinical data pre-processing

Missing values, particularly in the ‘cholesterol’ feature, are filled with the mean value and a total of 272 duplicate instances are removed from this dataset. The PID, Pname and Phoneno attributes are removed from the dataset. Feature correlations with the target variable are identified using a feature correlation heatmap, which informs feature selection for model training, as shown in figure 3. The dataset is nearly balanced, with 629 instances of heart disease and 561 without diseases, so no oversampling is needed that is shown in figure 4 and finally Min-Max scaling is used to normalize the feature values in the dataset.

ECG Image Data Pre-processing

All ECG images in this data set are 16x16 sizes; so that they are resized to a fixed size of 224x224 in order to meet

Table 1: Description of clinical dataset features

Feature Name	Data type	Description
Pid	Integer	Id in numeric
Pname	String	Patient name in character values
Phoneno	Integer	Phone number in numeric
Age	Integer	Age of patients in year
Sex	Integer	Describing gender male(1) and female(0)
Chest pain type	Integer	1 describes typical chest pain, 2 describes typical angina, 3 describes non-angina pain, 4 is asymptomatic
resting BP	Integer	Rest mode blood pressure level
Cholesterol	Integer	Concentration of cholesterol
fasting blood sugar	Integer	Fasting blood sugar >120 mg/dl represents 1 for true and 0 as false
resting ECG	Integer	ECG test result during rest is categorized as 0 for normal and 1 for abnormality
max heart rate	Integer	Maximum rate heart measured
exercise angina	Integer	0 depicting no angina induced and 1 describes angina induced
Old peak	Float	Exercise-induced ST –depression rate/rest state
ST slope	Integer	ST slope measured during exercise 0:normal, 1:unsloping, 2:flat, 3:down sloping
Target	Integer	1 (HD) and 0 (normal)

the input requirements of the EfficientNetB0 model. To enhance the diversity of the training set and improve model generalization, we employed image augmentation methods such as rotation, zoom, and flipping. Normalization

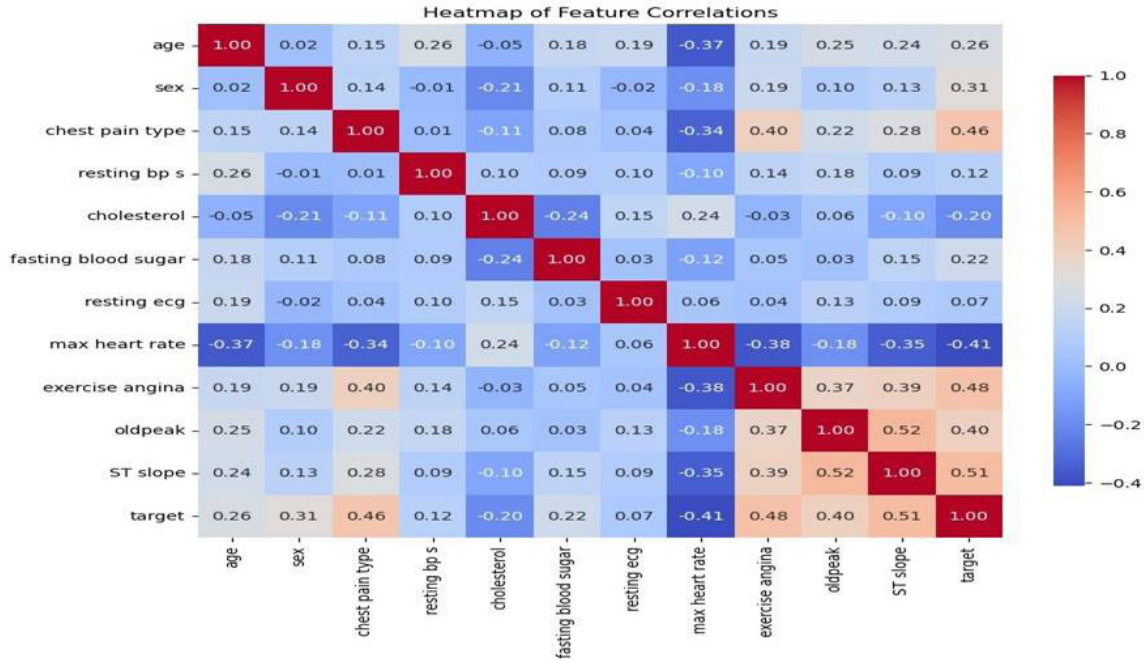


Figure 3: Feature correlation heatmap of the clinical dataset

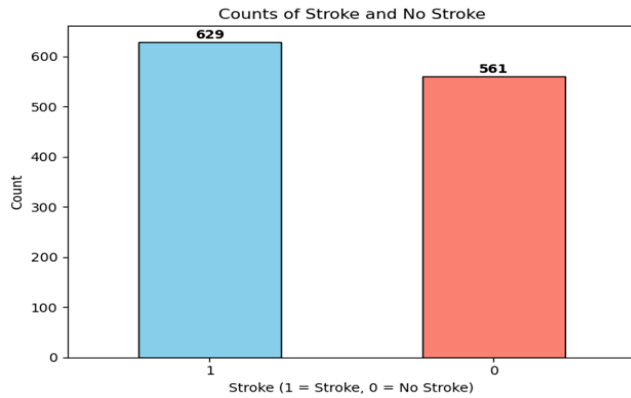


Figure 4: Represents stroke and no-stroke cases in clinical dataset

is applied to scaling the pixel values to a range (0 to 1) for better training stability and speed. And finally Image transformations like contrast adjusted, brightness maintained, and used filters to better highlighting features useful for the prediction of heart stroke.

Feature Selection with PSO

In this paper, we use Particle Swarm Optimization (PSO) algorithm for features selection from fused features. It is a population-based metaheuristic algorithm inspired by the social behaviour of birds flocking or fish schooling (Padmavathi, Bhat, & Karki, 2017). In PSO, each particle represents a potential solution—in this case, a binary feature subset and updates its position and velocity based on personal and global best positions using the formulas:

$$v_{i,j}^{(t+1)} = w \cdot v_{i,j}^{(t)} + c1 \cdot r1 \cdot (pbest_{i,j} - x_{i,j}) + c2 \cdot r2 \cdot (gbest_j - x_{i,j}) \quad (2)$$

and

$$x_i^{t+1} = x_i^t + x_{i,j}^{t+1} \quad (3)$$

where w is the inertia weight, $c1$ and $c2$ are cognitive and social acceleration coefficients, and $r1$, $r2$ are random numbers in $[0,1]$. For binary feature selection, a sigmoid transfer function is used to convert the velocity into a probability, guiding the binary position updates.

$$S(v_{i,j}) = \frac{1}{1 + e^{-v_{i,j}}} \quad (4)$$

Equation 4 maps the velocity to a value between 0 and 1, which is treated as a probability of selecting a feature.

$$x_{i,j}^{(t+1)} = \begin{cases} 1 & \text{if } rand() < S(v_{i,j}) \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Where $rand()$ generates a random number in $[0, 1]$ and this determines if a feature is selected (1) or not (0) for the next iteration.

The fitness function typically evaluates both classification accuracy and the number of selected features using equation allowing PSO to find an optimal trade-off between performance and dimensionality. This makes PSO an effective and computationally efficient method for selecting relevant features from combined clinical and ECG data, contributing to improved heart disease prediction performance.

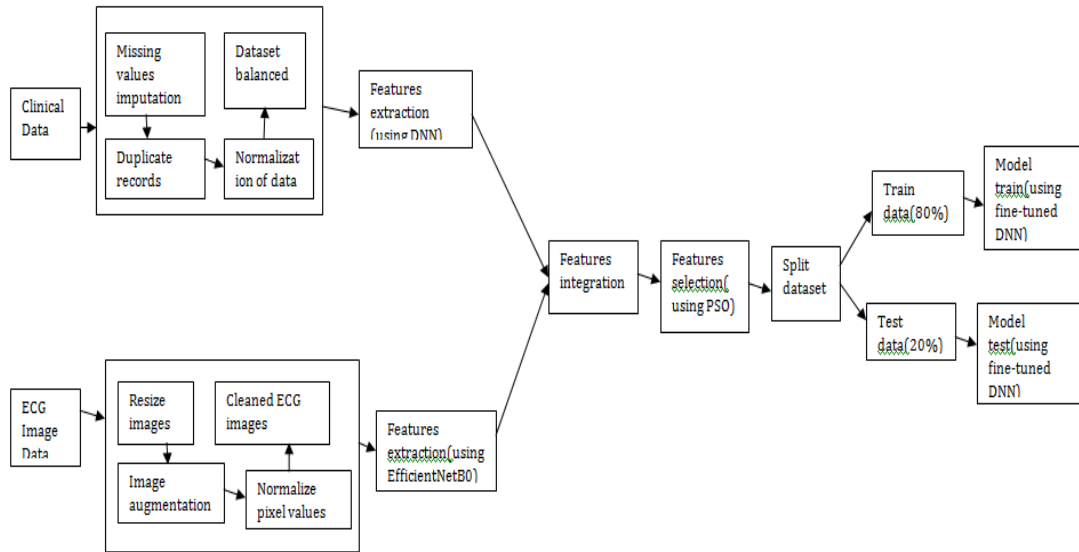


Figure 5: Workflow of proposed dual-modality deep learning model

$$Fitness_i = \alpha \cdot Accuracy + \beta \cdot \left(1 - \frac{\text{selected features}}{\text{Total features}}\right) \quad (6)$$

Here α indicates weight (importance) given to classification accuracy and β indicates weight (importance) given to feature reduction (i.e., selecting fewer features).

Proposed Methodology

The proposed model architecture in figure 5 shows pre-processing of both datasets, extracting features from both datasets, combining extracted features from both datasets, features selection, splitting the data into training(80%) and testing(20%) sets, building the model, and finally evaluating it with test data. A dense neural network is used to extract features from clinical dataset, an EfficientNetB0 neural network used to extract features from ECG images dataset, an early fusion is used to combine the features which are extracted from both datasets.

Algorithm

Dual-Modality Deep learning Model for Heart Stroke Prediction

Input

Clinical Dataset + ECG images Dataset

Output

Stroke Prediction (Yes or No)

Steps

- **For each instance in the clinical dataset**
Perform Data Pre-processing: Impute missing values, Remove duplicates, Normalize values, Standardize features.
Return refined clinical data

- **For each instance in the ECG image dataset**
Perform Image Pre-processing: Remove corrupted images, Resize images to 224×224 pixels, Convert images to RGB color format, Apply image augmentation (rotation, flipping, zooming), Normalize pixel values to [0, 1].
Return pre-processed ECG image data
- **For each refined dataset**
Combine clinical and ECG data: Extract features from ECG images using EfficientNetB0, Save EfficientNetB0 output as feature vectors, Concatenate clinical data with ECG feature vectors, ensuring row alignment.
Return combined dataset
- **Apply Particle Swarm Optimization (PSO) for Feature Selection**
Define a fitness function, Initialize particles with random feature subsets, Evaluate fitness for each particle, Update velocity and position of each particle, Select optimal subset of features from combined data
Return PSO-selected feature set
- **For each PSO-optimized dataset**
Perform 10-fold Cross-Validation If training data, then:
Train model using Dense Neural Network on selected features, Compile model with binary cross-entropy loss, Adam optimizer
Use metrics: accuracy, recall, precision, F1-score
Train model with callbacks (e.g., EarlyStopping)
Return trained model
Else (test data):
Apply trained model to test set, Calculate evaluation metrics: accuracy, recall, precision, F1-score and Plot: Confusion matrix, ROC curve with AUC, PR curve with AUC, Bar graph of accuracy, precision, recall, F1-score.

Return statistical results

Algorithm to Proposed Hybrid Dual-Modality Deep Learning Model

Performance Evaluation Metrics

The effectiveness of our proposed hybrid deep learning model on dual-modality is evaluated using these performance metrics:

Confusion Matrix

Displays True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values, helping assess the model's accuracy across different classes.

Accuracy

Measures the overall correctness of predictions, calculated as

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

Precision

Indicates the percentage of true positives out of all positive predictions, calculated as

$$\text{precision} = \frac{TP}{TP + FP} \quad (8)$$

Recall

Evaluates the model's sensitivity to real positives, calculated as

$$\text{recall} = \frac{TP}{TP + FN} \quad (9)$$

F1 Score

A balanced metric that combines precision and recall, calculated as

$$f1 - \text{score} = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}} \quad (10)$$

ROC Curve

Assesses the model's ability to distinguish between classes by plotting sensitivity against specificity across various thresholds.

AUC-ROC

Represents the area under the ROC curve, where a higher value indicates better discriminative ability.

PR Curve

Focuses on model performance with imbalanced datasets, plotting precision against recall across different thresholds.

Experimental Results

The proposed double-modality based hybrid deep learning model is developed using Python programming language with using Scikit-learn, TensorFlow, Keras, Matplotlib tools. We employ Keras-based deep learning models such as EfficientNetB0 for ECG image feature extraction, a dense neural network (DNN) for clinical data features extraction. We train the model on combining features of both datasets using fine-tuned DNN architecture. After pre-processing, the clinical dataset consists of 952 clinical data examples and an equal number of ECG image examples of same individuals. Here we take same patients clinical data and ECG images because of ensuring a balanced multi-modal input. We fine-tuned the DNN classifier with two hidden layers of 64, 32 neurons and ReLU as activation function in hidden layers and a sigmoid unit in the output layer because our prediction model is binary classification. We apply batchnormalization and dropout between the dense layers. The model is compiled with binary cross-entropy as the loss function and Adam optimizer for optimal results, trained for 10 epochs with a batch size of 32 with learning rate of 0.001. After fine-tuning the DNN model with specified parameters and after then we apply hyperparameters tuning, so that we achieved strong performance metrics with an accuracy of 86.13%, recall of 89%, precision of 87%, and an F1-score of 88%. Additionally, the ROC curve yielded an AUC value of 0.93, indicating excellent classification capability. This experiment was conducted using Jupyter Notebook on Anaconda3 software. Table 2 provides the hyperparameters used to train a model to optimize model performance.

Model Performance Metrics Analysis

A number of measures are used to assess model's predictive power for heart disease:

Confusion Matrix Analysis

The confusion matrix evaluates the accuracy of the model's predictions, such as predicting heart stroke. Figure 7 shows 89 true positives, 116 true negatives, 18 false positives, and 15 false negatives. The model performs well, with fewer false positives and false negatives of heart strokes.

Accuracy, Recall, Precision and F1 score Analysis

Our proposed model achieves 86.13% accuracy, 87.00% precision, 89.00% recall, and 88.00% F1-score, demonstrating its effectiveness in predicting cardiac stroke. Figure 8 shows these performance metrics:

		Predicted Values	
		Positive {1}	Negative {0}
Actual Values	Positive {1}	TP	FP
	Negative {0}	FN	TN

Figure 6: represents confusion matrix

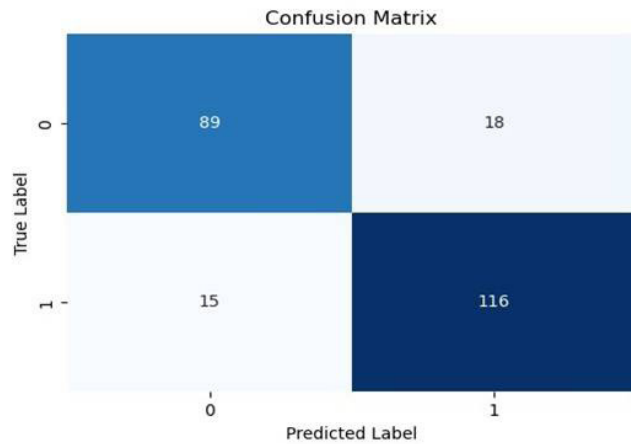


Figure 7: Results of Confusion Matrix

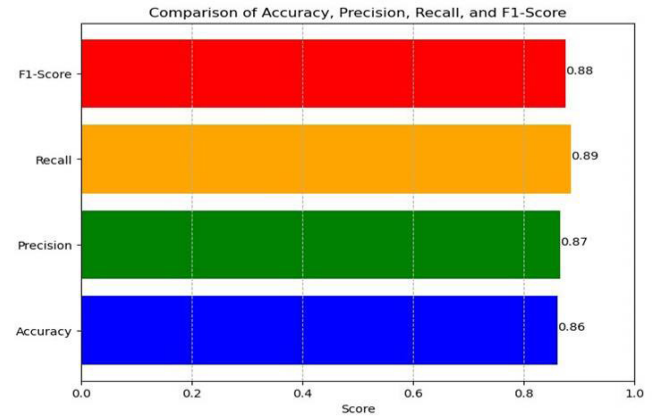


Figure 8: Experimental Results

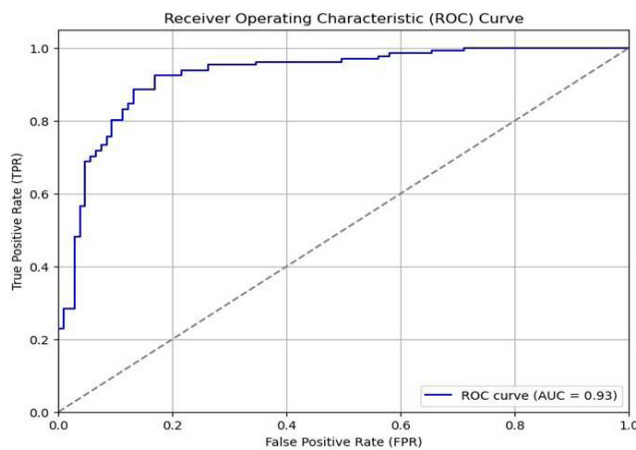


Figure 9: Results of ROC curve with AUC value

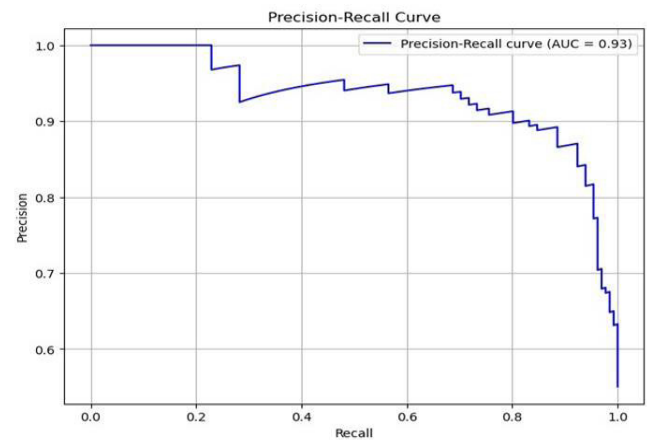


Figure 10: Results of PR curve with AUC value

ROC and AUC Analysis

The ROC curve in Figure 9 shows the model's performance across different decision thresholds, comparing the true positive rate (TPR) to the false positive rate (FPR). Since the ROC curve stays above the diagonal line, the model performs better than random guessing. With an AUC value close to 1, the model effectively distinguishes between positive and negative classes of the heart stroke.

Precision-Recall (PR) Curve Analysis

Figure 10 shows the PR curve, which raises sharply and then gradually decreases, indicating high precision and recall at a certain threshold. This suggests the model effectively detects true positives while minimizing false positives. A large area under the PR curve (closer to 1) indicates better performance.

Comparative Performance

We compare the performance of our proposed dual-modality deep learning model with single-modality. Table 3 shows that our model outperforms these approaches,

achieving 86.13% accuracy. Figure 11 shows the accuracy of highlighting the superior performance of our model.

Conclusion and Future Scope

This paper proposes a dual-modality based hybrid deep learning system for predicting cardiac disease with integrating clinical and ECG features to achieving an

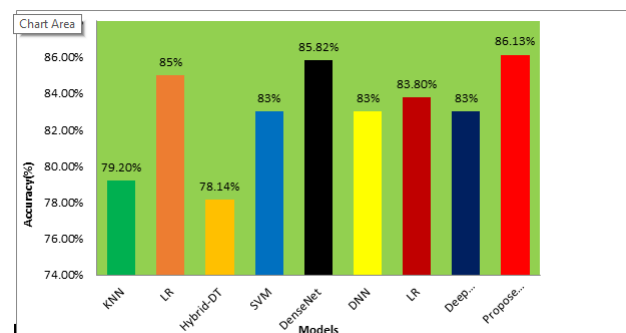


Figure 11: Comparison of different existing models accuracy with proposed model

Table 3: Comparison of different existing models with our proposed model

Author name, Reference	Method used	Accuracy
Khateeb N., et al.	KNN	79.20%
Dwivedi A.K.	LR	85%
Maji S., et al.	Hybrid-DT	78.14%
Singh A. et al.	SVM	83%
Xie Y., et al.	DenseNet (CNN)	85.82%
Cheon S., et al.	DNN	83%
Chicco D., et al.	LR	83.80%
Abdulwahab Ali Almazroi et al.	Deep learning (DNN) (Base Model)	83%
Proposed Model	Dual-modality deep learning model (Hybrid Dense Neural Network)	86.13%

accuracy of 86.13%, precision of 87%, recall of 89%, and F1 score of 88%. The integration of clinical data with ECG images improves model performance compared to single-modality tabular clinical or single-modality of image data approaches. The AUC value of 0.93 indicates the model's strong ability to distinguish between patients with having heart disease and without heart disease. The clinical features are extracted using a Dense Neural Network, while ECG image features are extracted using EfficientNetB0. And then features are combined in that combined features the most relevant features are selected using PSO algorithm and finally a fine-tuned Dense Neural Network (DNN) is used to build model and the model is evaluated using test data. Future research can explore additional modalities such as echocardiography results, blood tests and treadmill test graphs with using advanced deep learning models to extract features and apply feature fusion to further improve predictive performance. Additionally, different feature extraction techniques for ECG images and clinical data, along with the use of diverse deep learning architectures, can be investigated to optimize model accuracy and robustness.

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