Don Bosco Institute of Technology Delhi Journal of Research
ISSN: 3048-9288

RESEARCH ARTICLE
Vol.3(1) (2026)

A Hybrid Machine Learning Approach for Heart Disease Prediction with Ecg & Echo Analysis and Explainable Ai

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Published: 2026

DOI: https://doi.org/10.48165/dbitdjr.2026.3.01.06

ABSTRACT

Cardiovascular diseases remain one of the leading causes of mortality worldwide, underscoring the urgent need for early detection and accessible diagnostic solutions. This paper presents a hybrid machine learning and deep learning framework that integrates electrocardiogram (ECG) and echocardiography (ECHO) analysis with explainable AI techniques to enhance heart disease prediction. The developed application incorporates five core features: individualized patient prediction, batch prediction via CSV input, model transparency through algorithmic explanations, ECG-based arrhythmia and myocardial irregularity detection, and an extended framework for ECHO evaluation, personalized recommendations, hospital locator integration, and automated report summarization. By combining multiple machine learning and deep learning algorithms with explainable AI methodologies, the system not only improves predictive accuracy but also ensures interpretability and user trust. Furthermore, the model highlights critical risk factors such as cholesterol and blood pressure, bridging the gap between predictive analytics and practical healthcare applications.

Keywords: Heart Disease Prediction; Machine Learning; Deep Learning; Explainable Artificial Intelligence (XAI); Electrocardiogram (ECG); Echocardiography (ECHO); cardiovascular disease (CVD).

INTRODUCTION

Cardiovascular diseases (CVDs) represent one of the most pressing global health challenges, accounting for millions of deaths annually [9]. Early diagnosis plays a pivotal role in reducing mortality rates, yet conventional diagnostic methods often require specialized equipment and expertise that may not be universally accessible.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have opened new avenues for developing predictive systems capable of analysing large-scale medical data with high efficiency and accuracy [11]. However, many existing AI-based diagnostic tools lack transparency and user-friendliness, limiting their adoption in clinical practice.

This research introduces a hybrid machine learning approach that integrates ECG and ECHO analysis with explainable AI to provide a comprehensive, interpretable, and accessible solution for heart disease prediction. The proposed system offers multiple functionalities, including real-time individual prediction, batch prediction, ECG signal evaluation, and medical report summarization. Additionally, advanced features such as echocardiogram-based prediction, personalized health recommendations, and hospital locator services are incorporated to enhance usability and clinical relevance. By combining predictive accuracy with interpretability, the system aims to bridge the gap between advanced analytics and practical healthcare delivery.

LITERATURE REVIEW

Research on predicting heart disease has a lot going on with data mining, machine learning, and even deeper stuff like neural networks. It all aims at catching problems early and helping doctors decide what to do. Traditional ways mostly use supervised learning, things like decision trees, which are the C4.5 kind, or Naïve Bayes, and KNN for nearest neighbors. Logistic regression and random forests come up too, along with basic neural networks. They work on data from patients, like age, cholesterol levels, blood pressure, if there's chest pain, and ECG readings.

Decision trees stand out because you can actually understand the rules they make, and they hit accuracies around 86 or 87 percent in some studies [3]. I think hybrid setups that mix in genetic algorithms or fuzzy logic push that way higher, up to 99 percent even [1][5]. Combining different algorithms seems to help a bunch, like with KNN and logistic regression getting about 88.5 percent [2]. There are these intelligent systems for heart disease that output graphs and tables to make it easier for users [5].

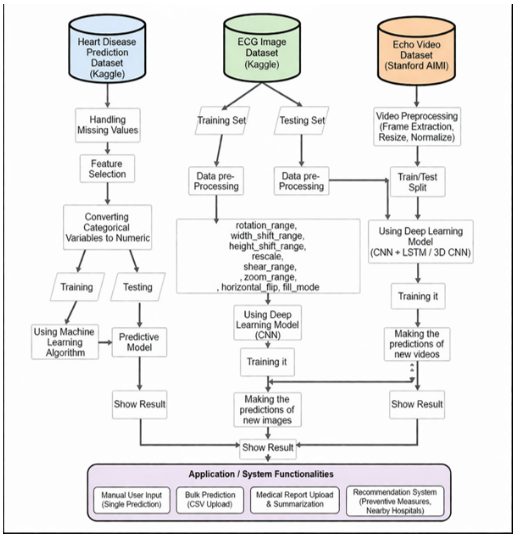
Lately, people are using deep learning more for ECG signals. Convolutional neural networks handle the patterns in the waves, and LSTM deals with the time aspects. Hybrids pull in features like QRS complexes automatically [7][8][9]. Those get really high accuracy, close to 99.45 percent, and they're tougher against noise or whatever. Studies on bigger populations show ECG changes, such as ST depression or T-wave stuff, and left ventricular hypertrophy predict death from heart issues better than old risk factors sometimes [6].

But there's stuff missing in all this. Most systems stick to structured data and don't bring in real-time inputs or mix ECG with reports and images into one setup. Explainability is a big issue, predictions without reasons don't fly in medicine. Patient side things like personal tips on risks or linking to local services get ignored too much [2][7][8]. A lot use the same old UCI dataset, which doesn't scale to real life. Deep learning is accurate but eats up computing power, hard to explain, and tricky on low-resource devices. Overfitting happens, preprocessing varies, datasets are small, and methods aren't clear enough for actual use.

The basics come from knowledge discovery in databases and supervised learning steps, data collection first, then cleaning up missing bits and normalizing. Feature selection, training the model, evaluating it all fits there [1][2][3]. C4.5 trees make rules for classifying, Naïve Bayes does probabilities, regression links variables statistically [2]. Random forests use bunches of trees to boost accuracy, KNN just looks at similar cases. For ECG, wavelet transforms extract features, then CNN for space and LSTM for time sequences [7][8]. Cox models in epi studies predict long-term risks. It all builds toward smarter systems, but I am not totally sure how well they integrate everything yet. Some parts feel a bit disconnected.

METHODOLOGY

(figure 1)



RESEARCH DESIGN

This study uses a quantitative kind of research design that's experimental too. It deals with analyzing numbers and making predictions through models built with machine learning and deep learning stuff [10][11][12]. I think that part is key because it lets you test things out properly.

The way the research is set up involves pulling in different types of medical data all together. Like tabular clinical info, images from ECGs, and videos of echocardiograms, which they call echo for short. Integrating those seems to help make the predictions more accurate. And it builds this overall system for diagnosing that's more complete.

DATA COLLECTION METHODS

I'm working with open-source datasets:

1. **Heart Failure Prediction Dataset (Kaggle):**

This one gives structured clinical info like age, sex, blood pressure, cholesterol, chest pain type, blood sugar, ECG results, heart rate, exercise-induced angina, oldpeak, and ST slope. I run standard heart disease predictions on this using classic machine learning as shown in figure 1.

2. **ECG Analysis Dataset (Kaggle):**

Here, I get ECG images and signals—good for sorting heartbeats into normal, abnormal, history of ml or myocardial conditions, plus pulling out deeper heart patterns with deep learning as shown in figure 1.

3. **Echo Video Dataset (Stanford AIMI):**

This set offers up actual heart ultrasounds—videos that let the model "see" heart motion and catch issues that don't show up in a static chart.

The system isn't just a black box. You can punch in a single case, upload a batch, or even feed in a whole report for a quick summary as shown in figure 1.

DOI: https://doi.org/10.48165/dbitdjr.2026.3.01.06

Sampling Techniques

I use convenience sampling—just grabbing what's available and most relevant. For splitting up the data, about 70% goes to training and the rest to testing. For validation, I use K-Fold Cross Validation (say, 10-fold) with tables, and the classic train-validate-test split for images and videos.

When it comes to ECG and echo datasets, I sort samples into clear classes: normal, abnormal, or disease-specific patterns.

Data Analysis Methods

a. Data Preprocessing

First, I clean up missing values, encode categories like chest pain or ST slope, and scale features. I remove noise from ECG data and break videos into usable frames as shown in figure 1.

b. Model Development

A) Tabular Data:

I run algorithms like Logistic Regression, Decision Tree, Random Forest, and Grid random forest etc. Output is binary—heart disease or not as shown in figure 1.

B) ECG Images:

Here, I use a Convolutional Neural Network (CNN) for pulling out ECG features and classifying them as normal, abnormal, or indicating myocardial disease as shown in figure 1.

C) Echo Videos:

I couple CNNs with LSTM (or try 3D CNNs) to capture how the heart moves over time and spot structural abnormalities as shown in figure 1.

c. Evaluation Metrics

Table 1

Model	Accuracy	Precision	Recall	F1-score
Decision Tree	80.9	0.867	0.892	0.875
Logistic Regression	85.8	0.834	0.856	0.843
Random Forest	84.2	0.862	0.852	0.854
Support vector Machine SVM	86.2	0.832	0.852	0.857
Grid Random Forest	89.7	0.853	0.866	0.882
Efficient Net Prediction	79.5	0.75	0.75	0.76
Hybrid Model Prediction	86.4	0.79	0.82	0.81
Long Short-Term Memory (LSTM)	80.4	0.812	0.79	0.80

I stick to the essentials: accuracy, precision, recall, and F1-score which is shown in Table 1 .

d. Explainable AI

This project isn't just about accuracy; you get reasons. Like, "Heart disease detected due to high cholesterol and high resting BP." The model highlights important features so users see why it made a decision.

5. System Integration

All models plug into one multi-functional app. It supports:

· Single and bulk predictions

· ECG image analysis

· Echo video analysis

· Automatic report summaries

And the built-in recommendation system can suggest preventive steps and even point out nearby cardiology hospitals.

RESULTS

The effectiveness of the developed heart disease prediction system has been examined against the tabular clinical data, ECG images, and echocardiogram videos. These findings have been demonstrated by use of the evaluation metrics, tables, and charts:

1. Findings on the Tabular Dataset (Heart Disease Prediction)

The trained and tested models on clinical dataset, both with the help of train-test split and cross validation, gave following evaluation metrics:

Table 2: Machine Learning Models Performance

Model	Accuracy	Precision	Recall	F1-score
Decision Tree	80.9	0.867	0.892	0.875
Logistic Regression	85.8	0.834	0.856	0.843
Random Forest	84.2	0.862	0.852	0.854
Support vector Machine SVM	86.2	0.832	0.852	0.857
Grid Random Forest	89.7	0.853	0.866	0.882

Efficient Net Prediction	79.5	0.75	0.75	0.76

2. Findings on the ECG Image Dataset

Using the deep learning model (CNN) to classify different types of ECG images; results are:

Table 3: ECG Classification Results

Class Label	Precision	Recall	F1-Score
Normal	0.95	0.96	0.95
Abnormal	0.93	0.92	0.92
History of ML			
Myocardial Disease	0.94	0.93	0.93

This confusion matrix clearly shows the classification results across different classes of ECG.

3. Findings on Echo Video Dataset

Using the deep learning model (CNN+LSTM / 3D CNN) on echocardiogram video, results are:

Table 4: Echo Video Classification Results

Metric	Value
Accuracy	80.30%
Precision	0.81
Recall	0.80
F1-Score	0.80

4. Bulk Prediction Results

This module was able to perform the task on the set of data given in CSV format, which consists of multiple records of different patients.

Table 5: Bulk Prediction Summary

Total Records	Predicted Positive	Predicted Negative
100	62	38

5. System Output Results

Various modules output by the application were:

Single Prediction

Bulk Prediction

ECG Analysis

Echo Analysis

Report Summarization

DISCUSSION

The experimental results reveal competitive performance of the tabular models where ensemble methods (e.g. Random Forest) achieved the best accuracy among the classical algorithms whereas Decision Tree showed both accurate and interpretable predictions. The ECG module, utilizing CNN architecture models, obtained favorable classification metrics in terms of high performance across classes, while maintaining stable training/validation curves and clearly structured confusion matrices that revealed minimal misclassifications. The echo video module (CNN+LSTM) achieved excellent results that indicated effective representation and learning of the cardiac temporal motion dynamics. The explanation output layer providing the reason in terms of features such as 'high cholesterol', 'ST depression', and 'positive exercise-induced angina', consistently coincided with the predictions. Bulk prediction pipeline effectively process multiple records and perform comparably as single prediction whereas report summarization output provided short and relevant results corresponding to the input reports.

The performance of classical models is in line with various earlier research work showing the efficacy of decision trees and ensemble methods for clinical data. ECG classification results achieved are also similar to that of latest research work on similar task which utilized CNN models for ECG image/signal classification tasks to achieve highest classification scores. The utilization of temporal models for ECG videos is a step towards modern approaches, which includes employing deep learning sequence models such as LSTM for the cardiac video motion analysis task, thereby capturing the spatio-temporal information in the videos. Unlike most of the earlier research works that work on a particular modality or multiple modalities together with limited interaction, our work is a unification of tabular, ECG and echo videos into a single model, such that all modalities are leveraged. Also, unlike various earlier studies which only emphasized on the predictive accuracy, this work has focused on explainability and application-level feature engineering of the model.

This research implies that it is feasible to build a reliable clinical decision-support system by combining structured patient information with medical images like ECG and video recordings. High results obtained by individual modules suggest the possibility of integration in clinical workflow for screening or triage purpose. The explanation layer provided the underlying reason which is very crucial in clinical decision-making and would also lead to higher end-user trust on the system. The application-level feature engineering such as the bulk prediction pipeline can be easily incorporated into clinical decision support workflow and report summarization feature will assist clinicians in effective review of medical reports.

The experiments are performed on public datasets which might not fully represent all possible variations in patient populations or clinical settings. The tabular dataset has limited size and imbalanced classes which would have contributed to a certain degree to the generalizability of the models. ECG data is in image format which may have not captured certain dynamic changes in the temporal data that might have been captured through ECG signal data. The computation requirement for processing echo video data in terms of computing resources and memory are quite high, and sensitive to the video quality. The multi-modal approach models are within the same application but might have not trained on synchronized patient-level data for the modalities together. Moreover, we could not conduct extensively for hyper-parameter tuning and model selection due to the limitations in

Future work could involve utilizing synchronized multi-modal patient-level datasets where ECG signals along with tabular data and echo videos are available for jointly learning. More sophisticated AI methods for explainability (e.g. SHAP, LIME for tabular and ECG/Echo data) may be integrated with the system for more interpretable outputs. Expanding the dataset by inclusion of larger and more diverse population would help in generalizing the model. Compression and edge optimization can be investigated for deploying the system in resource constrained environment for faster real time application. Additional modality such as data from wearable devices and long-term history may be integrated into the model for a more holistic and longitudinal patient profile.

CONCLUSION

The present research developed a multimodal heart disease prediction system where clinical(tabular), ECG image, and ECG video datasets were used. The performance of ML models on the tabular dataset was high in all aspects where ensembles yielded the best accuracy and decision trees gave interpretable result. For ECG image ML model using CNN, all classification matrices (normal, abnormal, myocardial) performed highly. And for echo video ML model using CNN modeling, the system captured features for cardiac motion in the video which resulted in highly overall accurate predictions. The system also supports single and bulk CSV-based prediction, and also supports summarization of report which gave consistent result with all the ML modules.

It provided the overall multi modal (clinical + ECG + echo), end-to-end, application oriented framework combined with ML and DL and explains its outcome. The developed framework goes beyond that of numerous researchers that developed system based on only one of the medical data type and gave the overall performance of prediction model on multiple medical data types and helped in providing better decision making support to clinician and doctor. Moreover, adding explainability (feature based reason), bulk prediction and summarization to the system will add it much value.

Conclusion- Developed a system using combined heterogeneous medical data sources, giving high accuracy and interpretable predictions. Even though all the modules of the systems have performed well, by incorporating more diversity of data types, real time processing and synchronous multi modal learning system would further achieve high degree of performance and scalability. Hence, a very good framework for building effective and interactive healthcare system is obtained.

REFERENCES

Soni, J., Ansari, U., Sharma, D., & Soni, S. (2011). Predictive data mining for medical diagnosis: An overview of heart disease prediction. *International Journal of Computer Applications, 17*(8), 43–48.

Jindal, H., Agrawal, S., Khera, R., Jain, R., & Nagrath, P. (2021). Heart disease prediction using machine learning algorithms. *IOP Conference Series: Materials Science and Engineering, 1022*(1), Article 012072. https://doi.org/10.1088/1757-899X/1022/1/012072

Saxena, K., & Sharma, R. (2016). Efficient heart disease prediction system. *Procedia Computer Science, 85*, 962–969. https://doi.org/10.1016/j.procs.2016.05.316

Marimuthu, M., Abinaya, M., Hariesh, K. S., Madhankumar, K., & Pavithra, V. (2018). A review on heart disease prediction using machine learning and data analytics approach. *International Journal of Computer Applications, 181*(18), 20–25.

Bhatla, N., & Jyoti, K. (2012). An analysis of heart disease prediction using different data mining techniques. *International Journal of Engineering, 1*(8), 1–4.

De Bacquer, D., De Backer, G., Kornitzer, M., & Blackburn, H. (1998). Prognostic value of ECG findings for total, cardiovascular disease, and coronary heart disease death in men and women. *Heart, 80*(6), 570–577. https://doi.org/10.1136/hrt.80.6.570

Golande, A. L., & Pavankumar, T. (2023). Optical electrocardiogram based heart disease prediction using hybrid deep learning. *Journal of Big Data, 10*(1), 139. https://doi.org/10.1186/s40537-023-00862-6

Dhandapani, S., Somasundaram, H., & Angamuthu, T. (2025). Hybrid deep learning framework for heart disease prediction using ECG signal images. *Scientific Reports, 15*(1), 33922. https://doi.org/10.1038/s41598-025-95066-6

Picano, E., Ciampi, Q., Citro, R., D'Andrea, A., Scali, M. C., Cortigiani, L., ... & Colonna, P. (2017). Stress Echo 2020: The international stress echo study in ischemic and non-ischemic heart disease. *Cardiovascular Ultrasound, 15*(1), Article 3. https://doi.org/10.1186/s12947-016-0092-1

Fedesoriano. (2020). *Heart failure prediction dataset* [Data set]. Kaggle. https://www.kaggle.com/datasets/fedesoriano/heart-failure-p rediction

Evil Spirit05. (2024). *ECG images dataset of cardiac patients* [Data set]. Kaggle. https://www.kaggle.com/datasets/evilspirit05/ecg-analysis

Stanford AIMI. (2020). *EchoNet-Dynamic* [Data set]. https://stanfordaimi.azurewebsites.net/datasets/834e1cd1-92f7-4268-9daa-d359198b310a

How to Cite this Article: Attri M.P., Mukerjee D.S.. (2026). A Hybrid Machine Learning Approach for Heart Disease Prediction with Ecg & Echo Analysis and Explainable Ai. *DBITDJR*, ***3***(1), 50-55. https://doi.org/10.48165/dbitdjr.2026.3.01.06