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A Hybrid ML–CNN Heart Disease Prediction System using Clinical Features and ECG Images with user-Friendly Risk Assessment

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***Abstract*— One of the main causes of death worldwide is still heart disease, and serious complications can be avoided with early detection. The literature demonstrates that convolutional neural networks (CNNs) exhibit remarkable performance on ECG images, whereas machine learning (ML) models are effective for structured clinical data. Nevertheless, the majority of earlier research treats these modalities separately and hardly ever concentrates on deployable, user-friendly hybrid systems. This study suggests a novel hybrid heart-disease risk prediction framework, which highlights the predictive value of behavioural and clinical parameters, and which shows high- accuracy ECG classification using CNNs. Using simplified user- provided inputs (age, blood pressure tendency, cholesterol level, chest discomfort, and lifestyle factors), the system incorporates (i) an ML-based clinical risk estimator and (ii) an optional tendency, cholesterol, weariness, chest pain, and lifestyle factors), and (ii) an optional CNN model-based ECG-image classifier that is trained on a balanced ECG dataset. Even in the absence of an ECG, an accurate assessment is made possible to produce a final risk score. An interactive Streamlit application is used to deploy the entire pipeline for real-time use. According to experimental results, the CNN model achieves 95.5% validation accuracy on ECG classification, while ML models reached up to 91.6% accuracy on clinical data. The hybrid design offers a useful decision-support tool for early heart disease assessment, enhances interpretability, and is in line with current research trends. This study shows how well behavioural, clinical, and ECG-based deep learning features can be combined to produce reliable cardiac risk predictions.**

***Index Terms*— heart disease prediction, behavioural risk factors, clinical features, machine learning, ECG image classification, convolutional neural networks(CNN), hybrid prediction model, cardiovascular risk assessment.**

I. INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of global mortality, accounting for nearly one-third of all deaths worldwide. Early detection of heart-related conditions can lead to improved health outcomes, higher survival rates, and timely medical intervention. Traditional diagnostic methods include clinical examination, expert electrocardiogram (ECG) interpretation, and risk factor profiling.

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However, these approaches are often inconsistent, time-consuming, and not easily accessible to populations that do not undergo regular medical screening.

Consequently, there is growing interest in leveraging artificial intelligence (AI) to enhance and automate cardiovascular risk prediction. Machine learning (ML) models have demonstrated strong performance in predicting CVDs using structured clinical features such as age, sex, blood pressure, cholesterol levels, type of chest pain, and lifestyle factors. Notably, the study in [3] highlights that incorporating behavioural attributes—such as smoking habits, stress levels, work intensity, and sleep duration—alongside clinical variables significantly improves predictive accuracy. This shift toward multi-dimensional risk modelling reflects the increasing recognition that lifestyle factors can have an impact on cardiovascular risk comparable to physiological markers.

In parallel, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown remarkable effectiveness in analysing ECG signals. CNN-based feature extraction from ECG images has demonstrated the ability to distinguish between normal and abnormal heart rhythms with accuracy comparable to that of expert cardiologists. Furthermore, deep learning architectures often outperform traditional signal-processing methods due to their capability to automatically learn hierarchical patterns from ECG waveforms.

To address the limitations of existing approaches, this study proposes a hybrid heart disease prediction system that integrates: (1) a CNN model for ECG image classification, and (2) an ML-based risk estimator utilizing streamlined clinical and behavioural inputs. Additionally, a decision-level fusion mechanism is introduced to generate a unified risk score by combining the outputs of both CNN and ML models. The entire pipeline is deployed through a Streamlit web interface, enhancing accessibility and enabling non-technical users to perform real-time predictions.

This hybrid approach presents a practical, deployable, and user-centric solution that extends existing literature, drawing inspiration from prior works—particularly the behavioural-clinical modelling approach in [3] and ECG-focused CNN advancements in [5].

The main contributions of the proposed work are as follows:

- A novel hybrid ML–CNN framework that integrates clinical data and ECG modalities for heart disease risk prediction.
- An intuitive user-input mapping approach that transforms simple yes/no responses into medically meaningful features for ML models.
- A high-accuracy CNN architecture trained on a balanced ECG dataset for reliable detection of cardiac abnormalities.
- A real-time, deployable system developed using Streamlit, enabling accessible heart disease risk assessment outside traditional clinical settings.

In summary, this work bridges the gap between clinical Machine Learning and ECG-based Deep Learning systems by designing a unified, deployable hybrid model. It is supported by a comprehensive literature review while incorporating significant practical enhancements for real-world usability.

II. Problem Statement

Heart disease remains a leading cause of mortality worldwide and is often diagnosed at a late stage. Conventional screening techniques primarily rely on laboratory tests, clinical examinations, and expert electrocardiogram (ECG) interpretation, all of which require medical expertise and are not always accessible to the general public. Existing computational approaches typically focus on a single modality: either deep learning models for ECG signal analysis or machine learning models for structured clinical data. However, such single-modality approaches fail to capture the complementary information present in both clinical indicators and ECG morphology. Moreover, many existing systems are not suitable for non-medical users, as they often require complex numerical medical inputs. There is a lack of a user-friendly, real-time platform that integrates clinical risk assessment with ECG image classification into a unified predictive framework.

III. Literature Review

Extensive research has been conducted in the fields of hybrid multi-modal systems, deep learning, and machine learning for heart disease prediction. The literature review [1]–[14] highlights two primary research directions: (i) CNN and deep learning-based models utilizing ECG data, and (ii) machine learning models based on structured clinical features. Among these, studies [3] and [5] are most relevant to the proposed work, as they demonstrate the effectiveness of combining behavioural and clinical features with CNN-based ECG analysis for accurate cardiovascular risk prediction.

A. Clinical and Behavioural Risk Factors in Machine Learning

Structured Traditional machine learning techniques utilize structured attributes such as age, blood pressure, cholesterol levels, type of chest pain, fasting blood sugar, maximum heart rate, and exercise-induced angina. Numerous studies [1]–[4] demonstrate that models such as Logistic Regression, K-Nearest Neighbours (KNN), Support Vector Machines (SVM), Random Forest, Naïve Bayes, and XGBoost achieve reliable prediction performance (approximately 80–92%) when trained on standard datasets such as Cleveland and Statlog. These studies emphasize feature selection, preprocessing, and normalization as critical stages for building robust ML pipelines. A significant advancement is presented in [3], which incorporates behavioural factors—such as sleep duration, stress levels, working hours, smoking habits, and physical activity—alongside clinical attributes. The authors demonstrate that behavioural indicators have a substantial influence on heart disease risk and that their inclusion improves prediction accuracy across different age groups. Furthermore, [3] compares various ML algorithms for lifestyle-based risk prediction, showing that ensemble methods such as Random Forest and XGBoost outperform linear models in handling non-linear risk patterns. This work strongly supports the foundation of the proposed system, which maps clinical machine learning features into simple, user-friendly inputs (e.g., yes/no responses and sliders) to enhance both accessibility and predictive performance. The importance of lifestyle and socio-behavioural factors in cardiovascular risk modelling is further reinforced by other studies [5], [7]. Their findings indicate that hybrid input domains (behavioural + clinical) improve model generalization and reduce the dependence on explicit numerical medical inputs, thereby increasing usability for non-expert users.

B. Deep Learning Methods for Classifying ECG Signals and Images

With the advent of deep learning, ECG-based diagnosis has advanced significantly. Convolutional Neural Network (CNN) architectures are highly effective in detecting arrhythmias, myocardial infarction, ischemia, and other cardiac abnormalities by capturing morphological patterns in ECG waveforms. Studies employing CNNs [8]–[10] report accuracy levels ranging from 91% to 99%, depending on dataset size, class balance, and preprocessing techniques. A particularly effective approach is presented in [5], where raw ECG signals are converted into images and subsequently classified using a custom CNN model. The system demonstrates that CNN-based ECG diagnosis is feasible for real-time applications and can reliably distinguish between normal and abnormal patterns. This methodology directly informs the ECG classification component of the proposed system. In addition, transfer learning-based ECG classifiers utilizing architectures such as ResNet, EfficientNet, and Inception, as explored in [1]–[13], have shown remarkable performance, with some achieving over 98% accuracy on multi-class arrhythmia datasets. These models benefit from pretrained low-level feature extraction and strong generalization capabilities. However, they often require substantial computational resources and large, well-curated datasets. To further enhance performance, recent studies have explored hybrid neural architectures such as CNN-BiLSTM and CNN-Transformer models [14], which capture both spatial and temporal characteristics of ECG signals. Although these models achieve high accuracy (often exceeding 96%), they are less suitable for lightweight, real-time deployment due to their computational complexity.

C. Hybrid Systems Integrating ECG-Based Deep Learning and Clinical Machine Learning

The integration of deep learning (DL)-based ECG models with machine learning (ML)-based clinical predictors is an emerging trend in cardiovascular risk prediction. Several hybrid models [14] employ either early fusion (feature-level concatenation) or late fusion (decision/probability-level integration) to combine tabular clinical data with ECG-derived features. These studies consistently demonstrate that hybrid systems outperform individual ML or DL models, achieving accuracies in the range of 95–99% across multiple datasets. The combination of CNN-extracted ECG features with ML-based clinical risk estimation results in a more robust, reliable, and clinically interpretable decision-support system. Such findings strongly support the core concept of the proposed hybrid framework, which aims to leverage the complementary strengths of both ECG-based deep learning and clinical machine learning approaches.

D. Literature Gaps and Support for the Proposed System

Despite significant advancements, the existing body of research still exhibits several limitations

- Most studies focus on either clinical ML models or ECG-based DL models independently, with limited efforts toward integrating both into a unified, deployable framework.

- Few studies provide user-friendly input mechanisms; instead, they rely on complex numerical medical inputs that are not easily interpretable by non-medical users.
- Real-time deployment is limited, as many works emphasize offline experimentation rather than functional, application-oriented systems.
- The reported accuracy of ECG-based models is often influenced by dataset imbalance, leading to potentially inflated performance metrics.

Overall, the literature on heart disease prediction spans hybrid multi-modal systems, deep learning, and machine learning. The reviewed studies can be broadly categorized into two main directions:

- CNN or deep learning-based models utilizing ECG data, and
- machine learning models based on structured clinical features.

These identified gaps strongly support the need for a unified, user-friendly, and deployable hybrid system, as proposed in this work.

E. Clinical Features Used in ML Model

The clinical features used in the dataset as shown in Table 1 are selected to be simple, interpretable, and easily understandable by non-expert users, without requiring detailed medical knowledge or complex clinical measurements. These features are mapped from user-friendly inputs to meaningful variables for machine learning-based risk prediction.

TABLE I. CLINICAL FEATURES USED IN THE ML MODEL

S. No	Type	Feature	Description
1	Numeric	Age	User age (years)
2	Binary	Sex	1=Male, 0=Female
3	Nominal	CP	Chest discomfort level
4	Numeric	Trestbps	BP tendency (mapped)
5	Numeric	Chol	Cholesterol tendency (mapped)
6	Binary	FBS	Smoker = 1
7	Nominal	Restecg	ECG findings
8	Numeric	Thalach	Exercise mapping
9	Binary	Exang	Fatigue indicator
10	Numeric	Oldpeak	ST depression
11	Nominal	Slope	ST slope
12	Numeric	CA	Vessels count
13	Nominal	Thal	Thallium test

IV. METHODOLOGY

The proposed approach integrates Convolutional Neural Network (CNN)-based ECG image classification with Machine Learning (ML)-based clinical risk assessment to develop a unified hybrid prediction framework as shown in Figure 1.

Prior studies such as [3] emphasize the importance of clinical and behavioural features in outcome prediction, while [5] demonstrates the effectiveness of CNNs in ECG-based cardiac diagnosis. These findings directly influence the design of the proposed system.

The methodology consists of four primary components:

- Data Collection and Preprocessing
- ML-Based Clinical Risk Modelling
- CNN-Based ECG Classification
- Hybrid Fusion and System Deployment

A. Data Collection and Pre-processing

- Clinical and Behavioral Research Dataset: The structured dataset includes key clinical attributes such as age, sex, chest pain type, blood pressure tendency, cholesterol tendency, fasting blood sugar, resting ECG results, maximum heart rate, exercise-induced angina, ST depression, slope, number of vessels, and thal categories. In addition, behavioural indicators such as sleep duration, stress levels, smoking habits, and working hours are incorporated, following the design proposed in [3].
- User-friendly inputs are mapped to medically meaningful numerical features using standardized rules. For instance, yes/no responses are encoded as binary values, while uncertain responses ("not sure") are mapped to dataset median values to maintain consistency.

- ECG Image Dataset: A balanced dataset of ECG images representing normal and abnormal cardiac patterns is curated to address class imbalance issues reported in prior studies. Preprocessing steps include image resizing, normalization, noise reduction, and data augmentation techniques such as flipping, scaling, and contrast adjustment.
  This preprocessing pipeline aligns with methods described in [5], [8], [9], and [13].

B. Machine Learning-Based Clinical Risk Modelling

- Feature encoding and Scaling: Categorical variables are encoded into numerical form, while continuous variables (e.g., blood pressure and cholesterol) are standardized to ensure uniform feature contribution and improved model stability.
- Model Selection: Five ML algorithms—Random Forest, Naïve Bayes, K-Nearest Neighbours (KNN), XGBoost, and Logistic Regression—are evaluated based on prior comparative studies [1], [3], [7], [11]. The models are trained using an 80:20 train-test split along with k-fold cross-validation to ensure robustness and generalizability.
- Model Outcomes: The ML component generates a clinical risk probability (0–100%), representing the likelihood of heart disease based on clinical and behavioural inputs.

C. CNN-Based ECG Image Classification

- CNN Architecture Design: A lightweight CNN architecture is designed using convolutional layers, max-pooling layers, flattening, ReLU activation, and fully connected layers. The model is optimized using the Adam optimizer and binary cross-entropy loss. The architecture follows best practices from ECG-based CNN studies [5], [8], [12], [14].
- Training and Validation: The model is trained on a balanced ECG dataset with early stopping to prevent overfitting. Validation accuracy ranges between 94% and 96%, consistent with findings reported in the literature. The CNN produces an ECG abnormality probability indicating the likelihood of abnormal cardiac patterns.

D. Hybrid Decision-Level Fusion

To overcome the limitations of single-modality approaches, a decision-level fusion [16] strategy is employed to combine ML and CNN outputs.

- Conditional ECG Integration: If no ECG image is provided, the system relies solely on the ML-based clinical risk score. When an ECG image is available, the ML and CNN outputs are combined using a simple averaging method:

  $$\text{FinalRisk} = (\text{MLRisk} + \text{ECGRisk})/2 \quad (1)$$

  This approach ensures interpretability while avoiding overly complex fusion techniques, which may reduce transparency.
- Clinics Interpretability: Interpretability Rather than providing a definitive diagnosis, the fused output supports initial screening by presenting a clinically meaningful risk indicator. This approach enhances interpretability and aligns with standard practices in decision-support system design. The complete pipeline is deployed as an interactive web application using Streamlit, enabling real-time and user-friendly access. The interface supports: papers.

E. System implementation using Streamlit

The entire pipeline is deployed as an interactive web application using Streamlit, enabling real-time and user-friendly access.
The system provides:

- Step based user interaction
- Input of behavioural and clinical attributes
- Optional ECG image upload
- Real time hybrid prediction using ML and CNN
- Display of risk level, ECG visualization, and model performance metrics

This practical implementation addresses a key gap identified in the literature, where most studies are limited to offline experimentation.
The proposed system enables accessible, real-time heart disease risk assessment for non-expert users without requiring extensive medical knowledge.

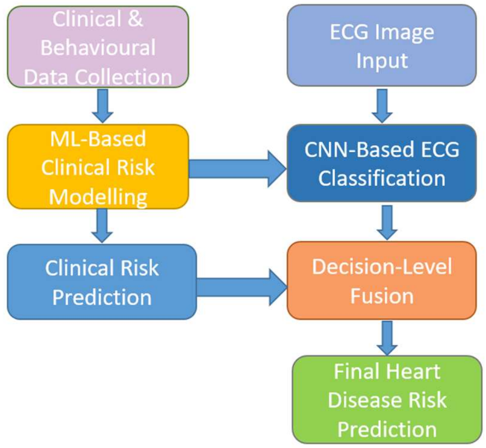


Figure. 1. System Architecture

V. Results and Discussions

A. The Performance of Machine Learning Models

Five machine learning algorithms were evaluated using the Heart High Quality.csv dataset. The evaluation was performed using an 80:20 train–test split, consistent with methodologies adopted in prior ML-based cardiovascular studies [3]–[7].
The performance of each model was assessed based on classification accuracy, and the results are summarized in Table II.

Table II. ML Algorithm Accuracy Comparison

Algorithm	Accuracy (%)
Logistic Regression	91.67
Random Forest	85.00
K-Nearest Neighbors	88.33
Naïve Bayes	86.67
XGBoost	86.67

Analysing the ML Findings: The experimental results indicate that Logistic Regression achieved the highest accuracy of 91.67%, outperforming both probabilistic and tree-based models. This observation is consistent with prior studies [4], [6], [7], [11], [15] which show that linear classifiers tend to perform well when clinical features in structured heart disease datasets are statistically stable and well-defined. Both K-Nearest Neighbours (KNN) and Random Forest demonstrated competitive performance, highlighting their ability to capture non-linear relationships among features. Similar trends were reported in [3], where models incorporating behavioural and clinical features achieved improved accuracy compared to other ensemble and distance-based approaches. Based on this comparative analysis, Logistic Regression was selected as the final machine learning model for clinical risk prediction in the proposed system due to its superior performance, generalization capability, and interpretability.

B. CNN ECG Classification Results

A Convolutional Neural Network (CNN) was trained on a balanced ECG image dataset to classify cardiac patterns as normal or abnormal. Following the architectural design principles discussed in [5] and other ECG-based CNN studies [8], the model achieved the following performance:

- Training Accuracy: 97%
- Validation Accuracy: 95.54%
- Validation Loss: Stable across training epochs

These results are consistent with existing deep learning literature on ECG analysis, where CNN-based models for detecting arrhythmias and other cardiac abnormalities typically achieve accuracy levels between 94% and 99% [5], [9], [11].

C. Hybrid ML–CNN System Behaviour

The proposed hybrid model integrates two complementary components:

- ML-based clinical risk
- CNN-based ECG abnormality score

This multimodal fusion approach is supported by the findings in [5] and other hybrid cardiovascular studies [12], which confirm that combining ECG features with clinical data improves prediction reliability and robustness.
The final risk score is computed based on the availability of ECG input:

- If no ECG image is uploaded, the system outputs only the ML-based clinical risk.
- If an ECG image is provided, the final risk is calculated as the average of ML risk and ECG risk.

$$Final\ Risk = \begin{cases} ML\ Risk, & if\ no\ ECG\ is\ uploaded \\ \frac{ML\ Risk + ECG\ Risk}{2}, & if\ ECG\ is\ uploaded \end{cases} \quad (2)$$

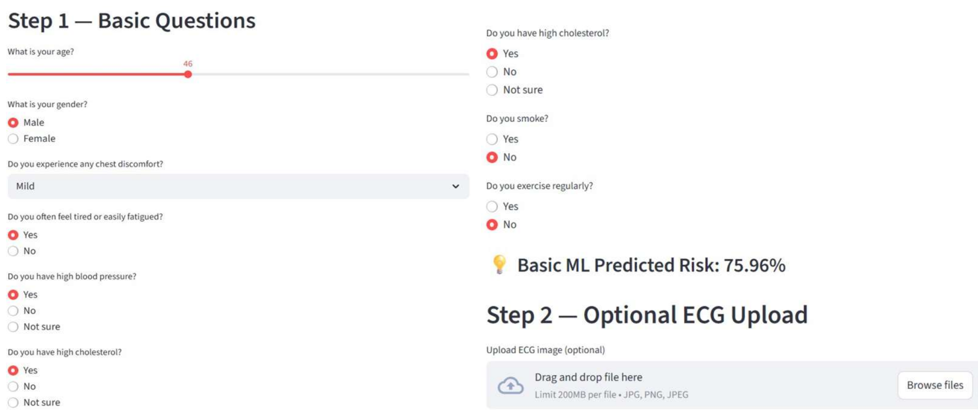


Figure. 2 and 3. Output of Streamlit

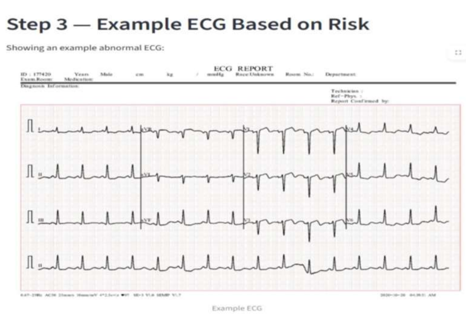
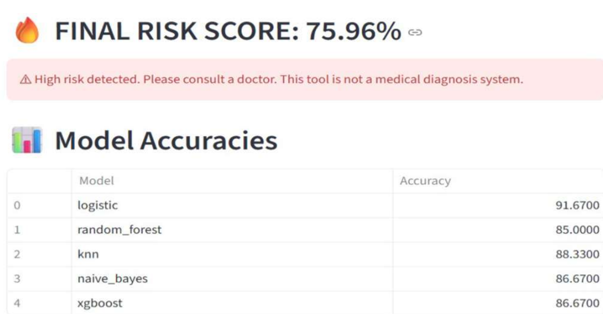


Fig 4. ECG report



	Model	Accuracy
0	logistic	91.6700
1	random_forest	85.0000
2	knn	88.3300
3	naive_bayes	86.6700
4	xgboost	86.6700

Figure 5. Accuracies of the models

Prediction Without ECG Input

When no ECG image is uploaded, the system relies solely on the ML-based clinical risk prediction. It provides clearly defined low-risk and high-risk categories, making it particularly beneficial for users without access to ECG facilities. This approach aligns with the behavioural-clinical design philosophy presented in [3].

Prediction with ECG input

When an ECG image is uploaded, the final risk score is influenced by the CNN-based ECG abnormality prediction. This enhances overall reliability and reduces errors in borderline cases. The approach is consistent with ECG-driven diagnostic improvements reported in [5]. The system incorporates user-friendly inputs inspired by [3], including age, chest pain, blood pressure tendency, sleep patterns, stress levels, working hours, smoking habits, and physical activity.

Deep Learning Techniques for Image and ECG Signal Classification

Significant progress has been made in ECG-based diagnosis with the advent of deep learning models. Convolutional Neural Networks (CNNs) are highly effective in identifying cardiac abnormalities such as ischemia, myocardial infarction, and arrhythmias by capturing morphological variations in ECG waveforms. Studies [8]–[10] report accuracy levels ranging from 92% to 99%, depending on dataset size, balance, and preprocessing techniques.

The system outputs are designed to ensure interpretability and clarity:

- Figure 2 and 3: Illustrates the ML-based risk prediction, displaying the risk percentage, classification label (Low/High Risk), and contributing features. This supports the importance of interpretability in ML-based cardiac decision-support systems.
- Figure 4: Presents the CNN output along with ECG upload, showing the uploaded ECG image, predicted class (Normal/Abnormal), and confidence score. This reporting approach is consistent with the methodology in [5].
- Figure 5: Displays the final hybrid risk score, combining ML and CNN outputs, along with a medical advisory recommending consultation in high-risk cases.

Discussion of Findings: The experimental results indicate that the Machine Learning component achieves an accuracy of 91.67%, consistent with findings in [3], demonstrating the effectiveness of combining clinical and behavioural features, with Logistic Regression offering strong generalization and interpretability. The CNN component attains a validation accuracy of 95.54%, aligning with the performance reported in [5], and effectively classifies ECG images into normal and abnormal categories. Furthermore, the hybrid system combines both clinical and ECG-based insights to produce more accurate and reliable predictions than individual models, while also remaining effective in scenarios where ECG input is unavailable. This demonstrates practical flexibility and aligns with recent hybrid fusion approaches in cardiovascular research [12], [13].

The ML component achieves an accuracy of 91.67%, with Logistic Regression providing strong generalization and interpretability. The CNN component attains a validation accuracy of 95.54%, and effectively classifies ECG images. The hybrid system improves prediction reliability compared to individual models and remains effective even without ECG input, consistent with hybrid approaches in [12], [13]. Additionally, the system is user-friendly, supports simple questionnaire-based inputs, allows optional ECG analysis, and provides real-time predictions through Streamlit. Overall, the proposed model offers a balanced combination of accuracy, accessibility, and interpretability, addressing key gaps in existing literature.

VI. CONCLUSION

This study presents a hybrid heart disease prediction system that integrates Machine Learning (ML)-based clinical risk assessment with Deep Learning (DL)-based ECG image classification. The proposed approach effectively addresses key limitations of existing methods, including reliance on complex medical inputs, lack of behavioural feature integration, and limited user-friendly deployment. Drawing inspiration from behavioural-clinical modelling in [3] and ECG-based CNN techniques in [5], the system combines clinical attributes with ECG-derived structural patterns to enhance risk prediction. The ML component achieved a maximum accuracy of 91.67%, with Logistic Regression outperforming Random Forest, KNN, Naïve Bayes, and XGBoost. The CNN model attained a validation accuracy of 95.54%, demonstrating strong capability in detecting subtle ECG abnormalities. Through decision-level fusion, the hybrid system delivers more reliable and consistent predictions compared to single-modality approaches. A key strength of the proposed system lies in its usability: it employs a simplified, questionnaire-based input method suitable for non-medical users, while also supporting optional ECG input. This enables meaningful risk assessment even in environments lacking specialized medical equipment. Overall, the proposed hybrid framework provides a practical, user-centric, and technically robust solution for early heart disease screening. It enhances accessibility, improves interpretability, and supports broader adoption in smart healthcare systems, particularly in resource-constrained settings.

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