International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
Conference "Innovation and Intelligence: A Multidisciplinary Research on Artificial Intelligence and its Contribution to Commerce and Beyond"
Organized by the IQAC, KHMW College of Commerce (December 2025)

Heart Disease Analysis of Smart Healthcare System using Data Mining and Machine Learning

[1]Akansha Jain, [2]Dr. Navin Kumar Agrawal
Ph.D. Scholar, Department of Electronics and Communication Engineering, Bhabha University, Bhopal[1]
Professor, Department of Electronics and Communication Engineering, Bhabha University, Bhopal[2]

Abstract
Heart disease is one of the leading causes of mortality worldwide, highlighting the importance of early diagnosis and continuous health monitoring. The rapid growth of smart healthcare systems, supported by electronic health records, wearable devices, and Internet of Things (IoT) technologies, has resulted in the generation of large volumes of medical data. Efficient analysis of this data is essential for timely and accurate disease prediction. This research presents an intelligent heart disease analysis framework for smart healthcare systems using data mining and machine learning techniques. Clinical attributes such as age, gender, blood pressure, cholesterol level, blood sugar, heart rate, and electrocardiographic results are analyzed to predict the presence of heart disease. Various machine learning classifiers are applied and evaluated to identify the most effective prediction model. Experimental results demonstrate that machine learning-based approaches significantly improve prediction accuracy and reliability compared to traditional diagnostic methods. The proposed system supports early detection, enhances clinical decision-making, and contributes to improved patient care within smart healthcare environments.

Keywords – Heart Disease Analysis, Smart Healthcare System, Data Mining, Machine Learning, Disease Prediction, Clinical Decision Support System

I. INTRODUCTION

Heart disease remains one of the most serious global health challenges, accounting for a large proportion of morbidity and mortality worldwide. Cardiovascular disorders, including coronary artery disease, heart failure, and arrhythmia, often develop silently over time and may remain undetected until they reach a critical stage. Early diagnosis and continuous monitoring are therefore essential for reducing mortality rates and improving patient outcomes. However, conventional diagnostic approaches primarily depend on clinical expertise and manual analysis of patient data, which can be time-consuming and susceptible to human error, particularly when dealing with large volumes of medical information [1. 2].

The advancement of smart healthcare systems has significantly transformed modern medical services by integrating technologies such as the Internet of Things (IoT), wearable sensors, electronic health records (EHRs), and cloud-based platforms. These systems enable real-time data collection and remote patient monitoring, generating vast amounts of structured and unstructured healthcare data. Efficient analysis of this data is crucial for extracting meaningful insights that can support timely diagnosis and personalized treatment. Data mining and machine learning techniques provide powerful tools to process complex medical datasets and uncover hidden patterns that may not be apparent through traditional analysis methods [3].

In recent years, data mining techniques such as classification, clustering, and association rule mining have been widely applied in healthcare analytics. Machine learning algorithms, including Logistic Regression, Decision Tree, Support Vector Machine, K-Nearest Neighbor, Random Forest, and Neural Networks, have demonstrated promising results in disease prediction and risk assessment. These models can learn from historical patient data and predict the likelihood of heart disease based on clinical parameters such as age, gender, blood pressure, cholesterol level, blood sugar, heart rate, and electrocardiographic results. Such predictive systems can assist healthcare professionals in making accurate and faster decisions, particularly in early-stage diagnosis [4, 5].

Despite the advantages of machine learning-based systems, several challenges still exist in heart disease analysis, including data imbalance, missing values, and variability in patient health conditions. Additionally, integrating predictive models into smart healthcare environments requires reliable, scalable, and interpretable solutions that can support real-time clinical decision-making. Addressing these challenges is essential to ensure the practical adoption of intelligent healthcare systems.

Figure 1: Structure of the Heart Disease Death Rate

This research focuses on the analysis of heart disease within a smart healthcare framework using data mining and machine learning techniques. The primary aim is to develop an intelligent predictive model that enhances diagnostic accuracy and supports early detection of cardiovascular diseases. By leveraging advanced analytics and historical clinical data, the proposed approach seeks to improve patient care, reduce healthcare costs, and contribute to the development of efficient and responsive smart healthcare systems [6].

II. LITEATURE REVIEW

El-Sofany et al. [1], presented a comprehensive machine learning-based approach for early heart disease prediction that combines rigorous feature selection, classifier comparison, and explainable AI techniques to improve diagnostic accuracy and interpretability. The authors employed multiple feature selection strategies—including chi-square, ANOVA, and mutual information—to derive three distinct feature subsets, ensuring that the most relevant clinical indicators were considered in model development. They evaluated ten machine learning classifiers, such as SVM, decision trees, random forests, bagging, and XGBoost, across both public and private heart disease datasets, and used the Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance. The results demonstrated that the XGBoost model trained on the optimal feature subset achieved superior performance with 97.57 % accuracy, 96.61 % sensitivity, 90.48 % specificity, and a 98 % AUC, outperforming many conventional techniques. Crucially, the study integrated an Explainable AI strategy using SHAP values to interpret the model's predictions, offering transparency into how individual features contributed to risk assessment. By combining high predictive performance with explainability, the work addresses key limitations of black-box models in clinical settings, enabling better understanding and trust among healthcare professionals. Furthermore, the authors extended their work toward practical application by developing a mobile app that delivers real-time predictions based on user-entered symptoms, highlighting the translational impact of their AI framework for heart disease detection.

Bhatt et al. [2], investigated the effectiveness of machine learning for heart disease prediction using a large real-world dataset and multiple classification algorithms to reduce misdiagnosis and improve diagnostic support. Their study employed techniques such as k-modes clustering and hypertuning through GridSearchCV to optimize model parameters across classifiers including decision trees, random forests, multilayer perceptrons (MLP), and XGBoost. Trained and evaluated on a dataset of approximately 70,000 instances with an 80:20 split, the models exhibited strong performance with accuracy values typically in the mid-80 % range. Among the evaluated models, the multilayer perceptron achieved the highest accuracy at 87.28 %, slightly outperforming other methods in classification tasks. This research also assessed models based on AUC metrics, where decision trees, random forests, XGBoost, and multilayer perceptrons all achieved AUC values around 0.94–0.95, demonstrating substantial discriminatory capability in identifying heart disease presence. Although the study did not explicitly incorporate explainability frameworks, it highlighted the potential of machine learning models to capture patterns in large clinical datasets and support medical decision-making. The findings underscore the value of model optimization and comparative evaluation in enhancing predictive performance, forming a foundation for further research that could integrate interpretability and multimodal data fusion for even more effective diagnostic systems.

O. Taylan et al. [3], to reduce the risk of myocardial infarction, cardiovascular disorders (CVDs) must be detected promptly and accurately. The complicated, ill-defined, and nonlinear relationships among the variables that contribute to CVDs necessitate the employment of artificial intelligence methods. These resources help in CVD classification and prediction. In this research, we suggest a methodology that uses machine learning (ML) techniques, such as support vector regression (SVR), multivariate adaptive regression splines, the M5Tree model, and neural networks for training, to predict, categorize, and increase the diagnostic accuracy of CVDs. Additionally, seventeen CVD risk factors are predicted using statistical and adaptive neuro-fuzzy methods, nearest neighbor/naive Bayes classifiers, and the adaptive neuro-fuzzy inference system (ANFIS). For both continuous and categorical factors that predict CVD risk, mixed-data transformation and classification techniques are used. We use a real CVD dataset that was gathered from a hospital to evaluate our hybrid models with current ML techniques. To ascertain the impact and display the crucial variables related to CVDs, such as the patient's age, cholesterol, and glucose levels, a sensitivity analysis is conducted. According to our findings, the suggested methodology performed better than popular statistical and machine learning techniques, demonstrating its adaptability and usefulness in CVD classification. According to our analysis, ANFIS has a 96.56% prediction accuracy for the training phase, while SVR has a 91.95% prediction accuracy. A thorough comparison of the outcomes for the aforementioned approaches is part of our study.

I. Sutedja et al. [4], Heart disease is currently one of the most deadly illnesses in the world. Since heart disease still has a comparatively high death rate, more intensive efforts are required to avoid it, such as by enhancing the development of a heart disease prediction model. Implementing a prediction comparison of multiple machine learning and deep learning models to determine if a person has heart disease or not is the aim of this study. Three machine learning models and three deep learning models make up the methodology employed in this study in order to predict heart disease with the maximum accuracy. Logistic Regression, Support Vector Machine (SVM), and Naïve Bayes are the machine learning models used in this study. Long Short Term Memory (LSTM), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) are the models used for the Deep Learning approach. The research yielded an accuracy of 86% for Logistic Regression, 88% for SVM, and 86% for Naïve Bayes. In the meantime, CNN obtains 84% accuracy, RNN 90%, and LSTM 84%. The research's conclusion is that the RNN model is the most accurate at 90%, making it the best choice for determining whether or not a person has heart disease.

Karna et al. [5], 17.9 million people die each year from cardiovascular diseases (CVDs). People can benefit from early prediction to alter their lifestyles and, if necessary, receive the appropriate medical treatment. Predicting whether a patient will develop a disease in the future is made much easier by the data that is available in the healthcare industry. In this examination, a few AI calculations, for example, Choice Tree (DT), Discriminant Investigation (DA), Strategic Relapse (LR), Credulous Bayes (NB), Backing Vector Machines (SVM), K-Closest Neighbors (KNN), and Gathering were prepared on Cleveland coronary illness dataset. Using 10-fold cross-validation both without and with Principal Component Analysis (PCA), the algorithms' performance was evaluated. With PCA using 9 components and Ensemble classifiers, LR achieved the highest accuracy of 85.8%, while with a Bagged tree and PCA using 10 components, it achieved an accuracy of 83.8 percent.

M. Ganesan et al. [6], discuss the challenges and strategies of the clinical decision support systems for heart disease prediction and diagnosis. This work mainly focuses on cardiovascular diseases in the Iranian community. A combination of support vector machine and binary particle swarm optimization is utilized for the prediction and classification process. Here SVM plays the dominant role, and it has utterly related to the data classification process and the binary particle swarm optimization technique assists in the feature selection process. The system performance measures are evaluated using the Isfahan Healthy Heart Program (IHHP) dataset, and it provides improved accuracy, sensitivity, and specificity measures in comparison to the commonly adopted classifiers for heart disease prediction. Support vector machines are the most effective method of classification technique widely used across several domains. It also has several applications relating to heart disease prediction and management processes. This method is much more effective across high-dimensional spaces and works well with the precise margin of separation. Additionally, it performs well with more dimensions than samples. Furthermore, this method is memory-efficient and computationally demanding. The presentation gauges at times corrupt with the uproarious and indistinct information.

Priyan et al. [7], provide an in-depth analysis of the statistical method showing its relevance to the data analysis model of logistic regressions. Logistic regression is a statistical method of data analysis applied across binary dependent variables. , The logistic regression methodology is an efficient approach for regression analysis. Logistic model parameters are estimated using logistic regression techniques. In layman's terms, the probability of an event in a logistic model is the linear combination of independent variables.

Prabal V. et al. [8], solve the major drawback behind the existing classification techniques. Further, it assesses the feasibility of the application of existing models in heart disease prediction. This work mainly focuses on reclassification tables along with sensitivity and specificity measures of the classification process. The deployment of these measures across this work improves the classification accuracy of heart disease. It makes use of the logistic regression models for the classification process. Carotid ultrasound measures are used to identify cardiovascular risk factors. Logistic regression models are used to differentiate the ultrasound measures and perform the classification process. Further, the regression models effectively identify the baseline factors and create a predictive regression.

III. SYMPTOMS OF HD

Dyspnea is often caused by strenuous exercise in healthy, well-trained people, and by continued exercise in normal people who are not accustomed to exercise, so it should be considered abnormal if this symptom occurs during breaks in physical work and is suddenly brought on. It is associated with all Huntington's diseases. It occurs only when resting, and almost always not when working hard. The effective onset of dyspnea is when there is increased awareness of breathing, caused by increased pain in the cardiovascular peak area, or a delay of more than 2 hours, a dull chest pain, and difficulty in taking enough air into the lungs [9].

2.1 Chest pain or discomfort

Chest pain is one of the most common symptoms of Huntington's disease, but it is difficult to determine whether it is caused by the heart or some other factor other than the heart. Chest pain is also one of the symptoms. People assume that chest pain is heart failure. If chest pain is caused by other disorders, heart disease is the most common and dangerous, but heart pain itself can be treated. It is used to describe irritation, pressure, tightness, numbness, and other discomfort in the chest, neck, and upper trunk, along with pain in the jaw, head, arms, etc. It can last for a few minutes, a few days, or even a week, depending on your expectations. The meaning of chest pain is very unclear, and there are some medical cases of HD that cause symptoms [10].

Syncope is described as "a loss of consciousness that causes a decrease in blood flow to the brain". Since around 2017, syncope has been defined as "a sudden, temporary loss of consciousness" and is a common symptom that many people experience only once in their lifetime and is not a serious illness. However, syncope can represent a dangerous, life-threatening condition. If syncope occurs, it must be diagnosed and treated. The causes of syncope are divided into two levels: neurological, metabolic, vasomotor, and cardiac. Syncope is a disease that causes sudden death. It can be caused by a variety of conditions that change the heartbeat. Palpitations, also known as "missing beats" or a fast, irregular heartbeat, are a common symptom. Some people with palpitations have arrhythmias, which are considered abnormal heart rhythms. Regardless of the cause, there are many different types of arrhythmias that can cause palpitations [11]. These side effects are normal for any illness. Weakness may be expected as an inability to function normally. Somnolence indicates lack of sleep or insomnia. Patients often fall asleep suddenly during the day. Indicative of HD, slurred displays indicate dysfunction of various organs of the body. Similarly, dizziness, lack of energy, fatigue, and lethargy usually require treatment to identify the specific cause. Disorders that cause nighttime sleep, such as restless legs syndrome and insomnia, are called somnolence [12].

IV. ML

ML proves invaluable, offering reproducible outcomes and the ability to learn from previous computations.

3.1 Supervised Learning

Supervised learning utilizes labeled data for classifying and solving problems, with regression and classification techniques as its two main branches. The regression analysis determines relationships among variables, indicating whether changes in explanatory variables are linked to changes in the dependent variable. In contrast, classification techniques assign objects to specific classes based on predefined criteria. Supervised learning methods represent the predominant approach in ML for predicting HD. These algorithms undergo training using a dataset comprising historical patient information, with each patient possessing a known label indicating the presence or absence of HD.

3.2 Unsupervised Learning

On the other hand, unsupervised learning lacks labeled data and introduces biases about the input's structure. When addressing CVD risk, regression techniques are essential to calculate an individual's risk based on actual numerical values associated with various risk factors (El-Hasnony et al. (2022)). In contrast, unsupervised learning algorithms analyze HD data without predefined labels, enabling them to uncover inherent patterns and relationships autonomously.

3.3 Reinforcement Learning

Within this framework, an agent is tasked with performing actions, and its effectiveness is contingent on its ability to comprehend the environment in which these actions occur. The agent maintains an internal state and interacts with the environment to achieve this understanding. A crucial aspect of this learning process involves using a reward function. The agent acquires knowledge about its environment by receiving positive or negative rewards based on its actions. The objective is to maximize positive rewards and minimize negative ones, encouraging the agent to learn and adapt over time. It is noteworthy that in reinforcement learning, there is no obligatory reliance on human experts possessing domain-specific knowledge. Applying this concept to healthcare, particularly in the context of HD management, reinforcement learning could prove valuable. For instance, an intelligent system could adapt its decision-making processes to optimize patient care by continuously learning from the patient's health data and treatment outcomes.

V. PROPSOED METHODOLOGY

The proposed research methodology is designed to develop an AI-based framework for early heart disease prediction by effectively integrating multimodal medical data, ensuring both high predictive accuracy and interpretability. The methodology consists of the following steps:

1. **Data Collection**
   - Acquire multimodal datasets including clinical records (age, blood pressure, cholesterol, etc.), laboratory tests, electrocardiogram (ECG) signals, and medical imaging (e.g., echocardiograms).
   - Ensure datasets are representative, balanced, and include both healthy and diagnosed patient samples.
2. **Data Preprocessing**
   - Clean and normalize the datasets to handle missing values, outliers, and noise.
   - Synchronize multimodal data to ensure temporal and patient-level alignment.
   - Encode categorical features and standardize numerical values for model compatibility.
3. **Exploratory Data Analysis (EDA)**
   - Perform statistical analysis to identify patterns, correlations, and trends across different modalities.

International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
Conference "Innovation and Intelligence: A Multidisciplinary Research on Artificial Intelligence and its Contribution to Commerce and Beyond"
Organized by the IQAC, KHMW College of Commerce (December 2025)

- Visualize data distributions and relationships between features and heart disease occurrence.

4. **Feature Extraction and Engineering**
   - Extract relevant features from each modality, such as heart rate variability from ECG, imaging biomarkers from echocardiograms, and biochemical markers from lab tests.
   - Apply dimensionality reduction techniques (e.g., PCA) if necessary to reduce redundancy and computational complexity.
5. **Multimodal Data Fusion**
   - Combine features from multiple modalities using feature-level, decision-level, or hybrid fusion strategies to capture complementary information.
   - Ensure the fused dataset preserves modality-specific characteristics while enabling holistic analysis.
6. **Model Development**
   - Train machine learning models (Random Forest, XGBoost, SVM) and deep learning models (CNNs for imaging, LSTMs for temporal data) on the fused dataset.
   - Optimize hyperparameters using techniques such as GridSearchCV or Bayesian optimization.
7. **Model Evaluation**
   - Evaluate the models using classification metrics: accuracy, precision, recall, F1-score, and ROC-AUC.
   - Perform cross-validation and test on unseen data to assess generalization and robustness.
8. **Explainable AI Integration**
   - Apply XAI techniques such as SHAP and LIME to interpret model predictions.
   - Identify and visualize the contribution of each feature or modality to individual and overall predictions, enhancing clinical trust.
9. **Result Analysis and Interpretation**
   - Compare the performance of multimodal models versus single-modal models to demonstrate the advantage of multimodal integration.
   - Analyze feature importance and decision explanations to provide actionable insights for clinicians.
10. **Framework Validation**
    - Validate the proposed framework on external datasets, if available, to assess reliability in real-world scenarios.
    - Document limitations, potential biases, and areas for improvement

VI. SIMULATION RESULTS

International Journal of Research and Technology (IJRT)

International Open-Access, Peer-Reviewed, Refereed, Online Journal

ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529

Conference "Innovation and Intelligence: A Multidisciplinary Research on Artificial Intelligence and its Contribution to Commerce and Beyond"

Organized by the IQAC, KHMW College of Commerce (December 2025)

Simulation Parameter

The accuracy of each fold determines how well the model has learned from the training data and how accurately it can predict new data. If the accuracy of a fold is high, it indicates that the model has successfully learned the underlying patterns in the data and can make accurate prediction. So, the accuracy can be measured according to Eq. 1

$$Accurancy = \frac{TN + TP}{TN + TP + FN + FP} \qquad (1)$$

For a diabetes classification problem, its measures include Precision-Recall and accuracy. The formula to derive these measures is given in Eq. 2 and Eq. 3.

$$\mathrm{Pr}ecision = \frac{TP}{TP + FP} \qquad (2)$$

$$\mathrm{Re}call = \frac{TP}{TP + FN} \qquad (3)$$

$$F1 - Score = \frac{2 * (\mathrm{Pr}ecision * \mathrm{Re}call)}{\mathrm{Pr}ecision + \mathrm{Re}call)} \qquad (4)$$

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

Fig. 1: Dataset

1. Histograms

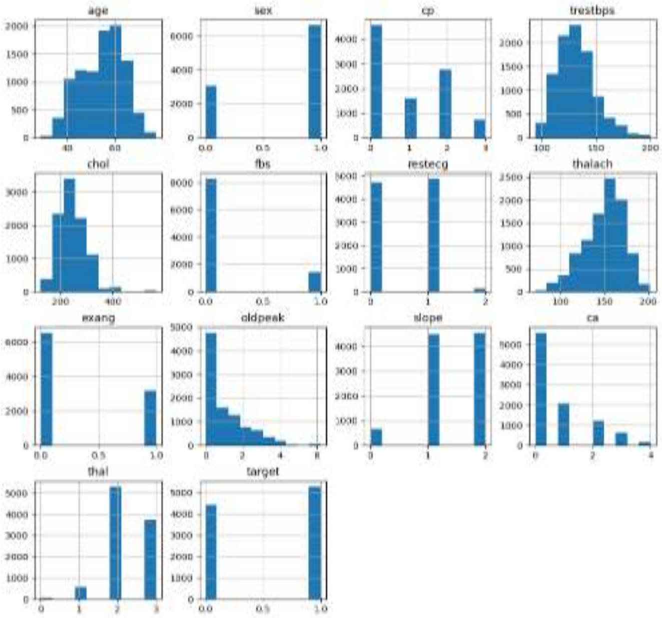

Fig. 2: Histograms of HD Dataset

2.Heart Disease Frequency for Age

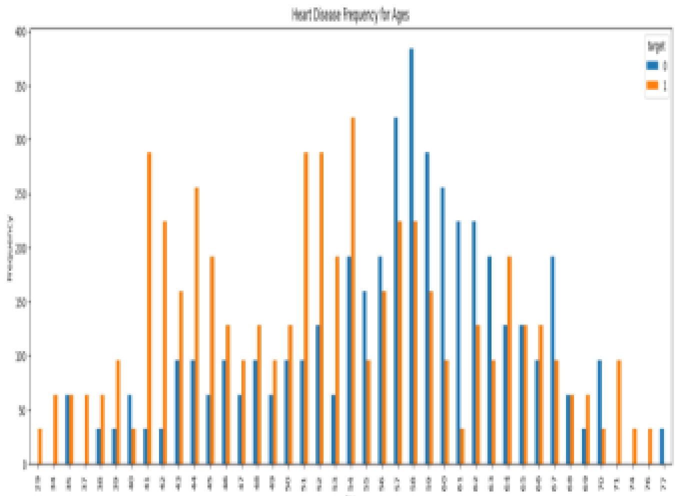

Fig. 3: Frequency of HD Dataset

International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
Conference "Innovation and Intelligence: A Multidisciplinary Research on Artificial Intelligence and its Contribution to Commerce and Beyond"
Organized by the IQAC, KHMW College of Commerce (December 2025)

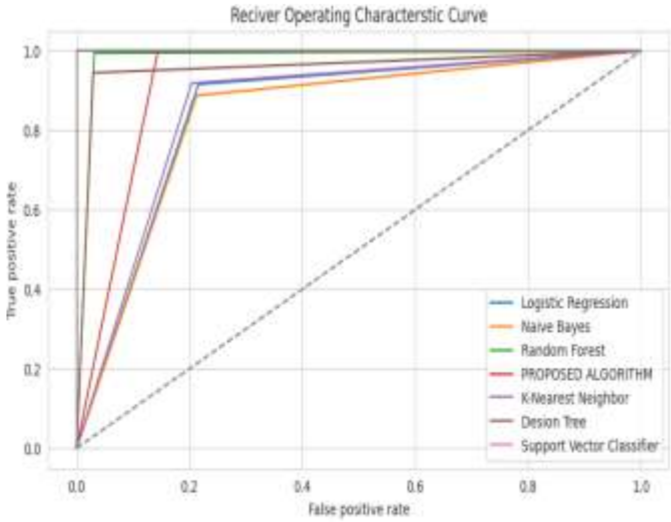

Fig. 4: Accuracy of Different ML Technique

VII. CONCLUSION

This research presented an intelligent framework for heart disease analysis within a smart healthcare system using data mining and machine learning techniques. By analyzing clinical and physiological parameters such as age, blood pressure, cholesterol level, blood sugar, heart rate, and electrocardiographic results, the proposed system effectively predicts the presence of heart disease. The application of machine learning algorithms demonstrates a significant improvement in diagnostic accuracy compared to traditional manual assessment methods.

The experimental analysis shows that machine learning-based models are capable of identifying complex patterns and relationships in medical data, enabling early detection of cardiovascular risks. The integration of data mining techniques enhances feature selection and data interpretation, leading to more reliable and efficient predictions. Such an approach supports healthcare professionals in making timely and informed clinical decisions while reducing diagnostic time and human error.

The proposed heart disease analysis system contributes to improved patient monitoring, preventive healthcare, and reduced mortality rates within smart healthcare environments. In the future, the system can be extended by incorporating real-time data from wearable devices, deep learning models, and explainable artificial intelligence techniques to further enhance prediction accuracy and clinical trust. The findings of this study highlight the potential of intelligent data-driven solutions in advancing smart healthcare systems and improving cardiovascular disease management.

REFRENCES

[1] H. El-Sofany, B. Bouallegue, and Y. M. Abd El-Latif, "A proposed technique for predicting heart disease using machine learning algorithms and an explainable AI method," *Scientific Reports*, vol. 14, pp. 1–18, 2024.

[2] C. M. Bhatt, P. Patel, T. Ghetia, and P. L. Mazzeo, "Effective heart disease prediction using machine learning techniques," *Journal of Medical Systems*, vol. 16, p. 88, 2023.

[3] O. Taylan, A. Alkabaa, H. Alqabbaa, E. Pamukçu and V. Leiva, "Early prediction in classification of cardiovascular diseases with machine learning neuro-fuzzy and statistical methods", *Biology*, vol. 12, no. 1, pp. 117, 2023.

[4] I. Sutedja, "Descriptive and predictive analysis on heart disease with machine learning and deep learning", *2021 3rd International Conference on Cybernetics and Intelligent System (ICORIS)*, pp. 1-6, 2021, October.

[5] Karna Vishnu Vardhana Reddy, Irraivan Elamvazuthi, Azrina Abd Aziz, Sivajothi Paramasivam and Hui Na Chua, "Heart Disease Risk Prediction using Machine Learning with Principal Component Analysis", International Conference on Intelligent and Advanced Systems (ICIAS), pp. 01-05, IEEE 2021.

[6] M. Ganesan and Dr. N. Sivakumar, "IoT based heart disease prediction and diagnosis model for healthcare using machine learning models", International Conference on System, Computation, Automation and Networking (ICSCAN), pp. 01-05, IEEE 2019.

[7] Priyan Malarvizhi Kumar, Usha Devi Gandhi, "A novel Internet of Things architecture with machine learning algorithm for early detection of heart diseases", Computers and Electrical Engineering, Vol.65, pp. 222–235, 2018.

[8] Prabal Verma, Sandeep K. Sood, "Cloud-centric IoT based disease diagnosis healthcare framework", Journal of Parallel Distribution Computer, Vol. 116, Issue 06, pp. 27-38, 2018.

[9] Amin Khatami and Abbas Khosravi, "Medical image analysis using wavelet transform and deep belief networks", Journal of Expert Systems with Applications, Vol. 3, Issue 4, pp. 190–198, 2017.

[10] Sanjay Kumar Sen, "Predicting and Diagnosing of Heart Disease using Machine Learning Algorithms", International Journal of Engineering and Computer Science (IJECS), Vol. 6, Issue 7, pp. 21623-21631, 2017.

[11] X Liu, X Wang, Q Su M Zhang and Y Zhu Q Wang, "A hybrid classification system for heart disease diagnosis based on the RFRS method", Computational and mathematical methods in medicine, pp. 01-11, 2017.

[12] Ashwini Shetty, Naik, C., "Different data mining approaches for predicting heart disease", International journal of innovative research in science, engineering and technology, Vol. 3, Issue 2, pp. 277–281, 2016.

[13] Aydin, S., "Comparison and evaluation data mining techniques in the diagnosis of heart disease", Indian journal of science and technology, Vol. 6, Issue 1, pp. 420–423, 2016.

[14] Bayasi, N. and Tekeste, "Low-power ECG-based processor for predicting ventricular arrhythmia", Journal of IEEE transactions on very large scale integration systems, Vol. 24, Issue 5, pp. 1962–1974, 2016.

[15] Berikol, B. and Yildiz, "Diagnosis of acute coronary syndrome with a support vector machine", Journal of Medical System, Vol. 40, Issue 4, pp. 11–18, 2016.