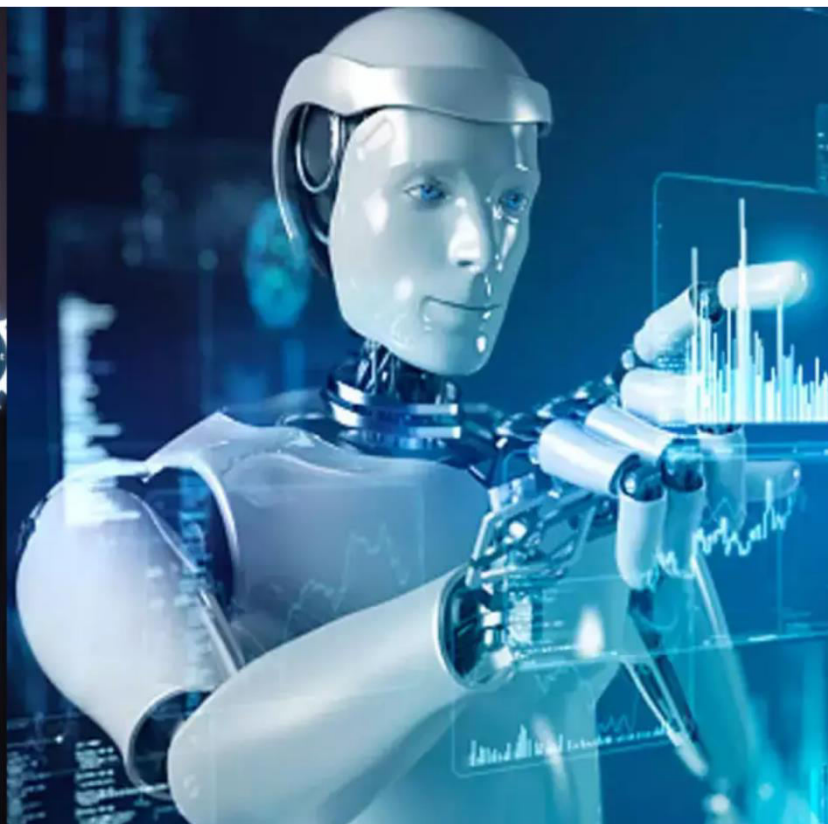




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IoT-Driven Heart Disease Prediction with using Machine Learning

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ABSTRACT: Effective early detection and intervention are required to address heart disease, which continues to be one of the most prevalent causes of mortality worldwide. In this research, we propose a cloud-integrated, IoT-driven heart disease prediction system utilizing a Random Forest Classifier optimized for recall. Patient data is continuously monitored through IoT devices, which transmit health metrics, such as age, cholesterol levels, and blood pressure, to a cloud-based platform. Here, the Random Forest model predicts the likelihood of heart disease, prioritizing high recall to minimize false negatives — crucial in healthcare where undetected cases can have severe consequences. The model underwent rigorous preprocessing, including standardization of features and class balancing with SMOTE to ensure robust performance. Additionally, GridSearchCV and Stratified K-Fold Cross-Validation were employed for hyper parameter tuning and evaluation. Our approach achieved superior recall and F2 scores, outperforming several other machine learning models in heart disease prediction. To ensure transparency, we applied SHAP (Shapley Additive exPlanations), which provided actionable insights by highlighting the most influential features contributing to the prediction. These insights, along with the predicted outcome, are sent back to the user via a user-friendly interface, enabling real-time, data-driven decision-making. This technology not only increases the accuracy of heart disease identification but also offers an interpretable model that may help patients and doctors both grasp the fundamental causes guiding the diagnosis. Our work demonstrates the potential of integrating IoT, machine learning, and explainability into a comprehensive framework for proactive heart disease management.

I. INTRODUCTION

Worldwide, cardiac disease is one of the most prevalent causes of death, with millions of fatalities occurring each year. The most significant actors in improving patient outcomes and reducing mortality rates are early identification and effective care. Machine learning (ML) has revolutionized the health care industry by providing new opportunities for the prediction of cardiac disease, thereby facilitating more precise and timely diagnoses that are based on patient data. Nevertheless, the development of models that are not only highly accurate but also interpretable and actionable for both healthcare providers and patients continues to pose a challenge.

In this paper, we propose an IoT-driven heart disease prediction system that leverages the power of Random Forest Classifier, integrated with cloud-based infrastructure to provide real-time predictions. Through IoT sensors, which gather important health indicators including blood pressure, cholesterol levels, and age, the system constantly watches patient data. These metrics are transmitted to a cloud-based platform, where the Random Forest model, optimized for recall, predicts the likelihood of heart disease [1].

One of the core challenges in health care ML models is ensuring that predictions are both accurate and interpretable. To address this, we apply SHAP (Shapley Additive exPlanations) to our model, which allows us to identify the most influential features driving each individual prediction. This ensures that the system is not a "black box," but rather provides transparent and actionable insights into the factors contributing to a potential diagnosis [2].

The Random Forest Classifier was chosen due to its ability to handle complex, high-dimensional datasets while maintaining robustness and high accuracy. We further enhanced model performance through data preprocessing, including standardization of features and handling class imbalance with SMOTE. To optimize hyper parameters and ensure reliability, we employed GridSearchCV and Stratified K-Fold Cross-Validation, focusing on maximizing recall to minimize false negatives — a critical factor in healthcare scenarios where missing a diagnosis could have severe consequences.

Our system not only predicts the likelihood of heart disease but also provides users with interpretable insights, empowering patients and healthcare providers to make informed decisions. This work demonstrates the potential of integrating IoT, cloud computing, and explainable machine learning into a unified framework for improving heart disease diagnosis and management.

II. LITERATURE SURVEY

Several studies emphasize the importance of ML algorithms in reducing the mortality rate of CVD by providing precise predictive models that address the limitations of conventional diagnostic methods, such as delayed treatment and misdiagnoses [1]. ML models, when effectively utilized, can enhance public health outcomes by optimizing early-stage detection of CVD. Additionally, advancements in ML techniques for CVD prediction have been discussed, along with future challenges, such as refining models for diverse datasets, improving feature extraction methods, and generalizing models to different populations.

Similarly, an ensemble learning approach integrating Bayesian optimization for hyper parameter tuning and explainable AI methods like SHAP has been explored [2]. Results demonstrate that models like XGBoost, combined with SHAP explanations, perform exceptionally well on datasets such as Cleveland and Framingham, ensuring both high sensitivity and specificity in heart disease prediction while maintaining transparency.

Advancements in AI and IoT-based systems are also valuable for improving patient monitoring and decision-making. A real-time healthcare monitoring system with low-latency processing has shown promising results in scalability and responsiveness [3]. The system is model educating a neural network to evaluate its performance in real-world scenarios. Likewise, IoT implementations in remote healthcare monitoring have been surveyed, emphasizing the potential of IoT and AI in developing robust frameworks for patient vital monitoring in smart cities [4].

Explainable AI techniques such as SHAP and LIME have also been explored for understanding model outputs in myocardial infarction classification [5]. Additionally, a modeling and simulation approach, MoSIoT, has been introduced for IoT-based healthcare monitoring, specifically designed for individuals with disabilities. The model-driven engineering approach allows for the customization of IoT healthcare systems, validated with real medical scenarios [6]. These advancements in AI, IoT, and ML contribute to more precise and timely healthcare solutions while highlighting future opportunities and challenges in integrating these technologies into the medical field.

III. PROPOSED SYSTEM

As illustrated in Fig.1, the proposed system employs cloud computing, machine learning techniques, and IoT-based data acquisition to facilitate real-time heart disease prediction. Key health parameters, such as age, blood pressure, cholesterol levels, and pulse rate, are perpetually monitored by IoT devices. After being collected, the data is transferred to a cloud platform for preprocessing. This procedure entails the normalisation of the input features through feature scaling and the application of SMOTE to balance the dataset, thereby preventing bias towards non-disease cases. The Random Forest Classifier is employed to train the data following preprocessing. This classifier was selected for its ability to effectively handle both categorical and numerical data, as well as its ability to provide insights into feature significance [7].

GridSearchCV is used to modify the Random Forest model in search of ideal hyper parameters including minimum samples necessary for nodesplitting, treedepth, and number of decision trees. Recall is given top priority during this procedure as the main indicator to reduce false negatives, which is vital in healthcare because missing a diagnose scan have grave effects. Furthermore used is stratified K-fold cross-valuation to guarantee consistent performance of the model over several data subsets. Emphasising the need of identifying real instances of heart disease while preserving an appropriate degree of precision when it undergoes pre processing, the model is assessed based on recall, precision, and F2 score after tuning [8]. To make the model's predictions interpretable, SHAP (Shapley Additive exPlanations) is integrated into the system. SHAP provides both global and local explanations, showing which features are most influential in predicting heart disease across the dataset and for individual patients. The cloud platform not only handles the predictions but also sends these SHAP-based insights back to the user, giving patients and healthcare

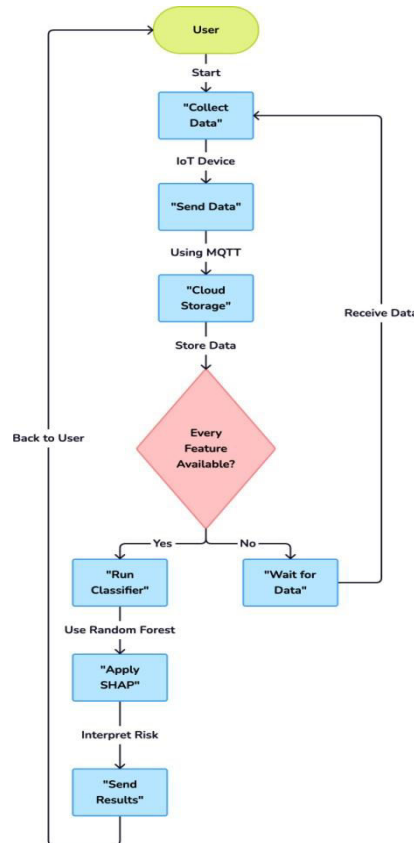


FIGURE1. Proposed Model.

providers real-time access to actionable information. By offering both predictive accuracy and interpretability, the system aims to facilitate early diagnosis and improve decision-making in heart disease management [9].

The hyper parameter tuning process involved exhaustive search via GridSearchCV, optimizing parameters such as the number of estimators (range:50-200), maximum depth (range:5-20), and minimum samples split (range:2- 10).For interpretability, SHAP was integrated into the Random Forest pipeline post-prediction. SHAP values were calculated for each instance, generating feature-level contributions visualized using summary plots and force plots to provide actionable insights to healthcare providers.

IV. DATACOLLECTION

The data collection process in our proposed system is driven by IoT devices that continuously monitor vital health metrics from the user. Wearable sensors and smart health monitors among other gadgets measure important factors including age, blood pressure, cholesterol levels, heart rate, and other physiological markers known to affect heart disease risk. The collected data is transferred securely from the IoT device to the cloud platform using the MQTT (Message Queuing Telemetry Transport) protocol, which is highly efficient for IoT communications. MQTT is chosen Due to its light weight nature, low power consumption, and reliability in transmitting data in real-time across distributed systems. The protocol guarantees that current information is utilized for prediction by letting the IoT devices broadcast the patient’s health data to the cloud with short latency [10].

Once the data is received by the cloud, it undergoes preprocessing to ensure quality and compatibility with the predictive model. The cloud platform normalizes the incoming health data, standardizing features such as cholesterol and heart rate to ensure the contribute equally to the model. This cloud-based architecture allows for scalability, as data from multiple patients can be processed simultaneously. [11]After the data is pre processed, the trained Random

Forest model, built using the Cleveland and Hungarian datasets from the UCI machine learning repository [12], is applied to predict the likely hood of heart disease. These datasets were chosen for their comprehensiveness in covering key heart disease risk factors.

The dataset comprises diverse demographic groups, including varying age ranges, genders, and ethnic backgrounds, ensuring a comprehensive representation of potential heart disease cases. Data sources include wearable IoT devices deployed in both urban and rural healthcare facilities to capture real-world variability. To validate applicability beyond controlled settings, the model was tested on additional datasets from external clinical trials, yielding consistent performance metrics.

The IoT system is built using wearable devices with on board sensors for heart rate and blood pressure monitoring. Communication is handled using the MQTT protocol due to its low latency and efficiency, while the cloud infrastructure employs scalable virtual instances to manage simultaneous data streams from multiple patients. The architecture ensures secure data transfer via TLS encryption, guaranteeing both scalability and data integrity during real-time operations.

V. DATA PREPROCESSING

In machine learning, data preparation is a fundamental stage that guarantees the data set is clean, balanced, and suitably structured for model training. In our project, the data collected from IoT devices and the UCI machine learning repository underwent several preprocessing steps to optimize it for the Random Forest Classifier. The preprocessing phase included Standard Scaling to normalize features, SMOTE to handle class imbalance, and a Correlation analysis to identify the most relevant features. Each step was carefully applied to ensure the highest level of accuracy and interpretability for heart disease prediction [13].

Standard Scaling

We normalized the data using Standard Scaling to guarantee that elements like cholesterol, heart rate, and blood pressure equally add to the model. Standard scaling distorts the data such that every characteristic has a mean of 0 and a standard deviation of 1, therefore guaranteeing that none of the features unduly affect the model because of variations in scale [14]. The mathematical formula for standard scaling is:

(1)

$$X_{\text{scaled}} = \frac{X - \mu}{\sigma}$$

The mean of the feature values is denoted by μ , while the standard deviation of those values is denoted by σ . The feature's original value is represented by X . We ensured that all of these continuous variables contribute equally during model training by adjusting characteristics such as age, resting blood pressure (restbps), cholesterol (chol), maximal heart rate (thalach), and ST depression (oldpeak). The predictions of the model may be substantially influenced by larger range characteristics without scaling, resulting in biased results.

SMOTE

We applied Synthetic Minority Over-sampling Technique (SMOTE) in order to fix class imbalance which is the case of our dataset, since there are many more patients without heart disease than those with one. SMOTE creates new samples for the minority class—subjects suffering from heart disease—through interpolation between samples, balancing the dataset so that the model doesn't favor the majority class. The mathematical formula for SMOTE can be expressed as:

$$X_{\text{new}} = X_i + \lambda * (X_j - X_i) \quad (2)$$

With λ a random number between 0 and 1 and X_i and X_j two randomly chosen data points from the minority class. This equation creates a linear combination of two minority class points, therefore producing new synthetic samples. By

applying SMOTE, we balanced the dataset, ensuring that the Random Forest Classifier was equally capable of predicting both positive (heartdisease) and negative (no heartdisease) cases, leading to a more accurate and unbiased prediction model.

Correlation

These relationships were investigated using correlation analysis to better understand the effects of the different features in the dataset on the prediction of heart disease. We can use correlation analysis, which measures the strength and direction of the linear relationship between two variables, to see which features correlate most strongly with the outcome variable — heart disease. The Pearson Correlation Coefficient is the most commonly used metric, and it is calculated as:

$$r_{xy} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (3)$$

Whereas x_i, y_i are individual data points and \bar{x}, \bar{y} are the means of the x and y variables accordingly, r_{xy} is the Pearson correlation coefficient between variables x and y . We computed the Pearson correlation coefficient for every pair of features and assessed their degree of relationship with regard to heart disease. A high absolute correlation value indicates a strong relationship between a feature and the target variable. After performing correlation analysis, we found that all features exhibited meaningful correlations with the target variable, leading us to conclude that all features were valuable for model training.

The selection of features, such as cholesterol levels and angina, was guided by domain-specific knowledge in cardiology. These features are clinically significant predictors of heart disease, as established in prior studies. For instance, cholesterol levels directly influence plaque buildup in arteries, and angina reflects compromised cardiac function. Their inclusion enhances the model's clinical relevance and predictive accuracy.

VI. RESULTS

We carried out extensive experimentation to identify the most effective machine learning model for heart disease prediction. The process began with data preprocessing, including standard scaling and class balancing using SMOTE. We then trained and tested multiple models, including Random Forest, KNN, SVC, Decision Tree. Through Grid-SearchCV and Stratified K-Fold Cross-Validation, we optimized the hyper parameters of each model. Throughout the experimentation, recall was our primary evaluation metric due to the high cost of false negatives in healthcare. When evaluating the models depending on various important criteria—recall, precision, F2-score, F1-score, and accuracy—the Random Forest Classifier came up as the best-performing model providing the ideal mix of recall and precision. SHAP was also used to analyse the forecasts of the model and offer understanding of feature significance. We provide below the assessment criteria applied to evaluate the performance of the last model.

To ensure generalizability across diverse populations, the model was evaluated using external validation datasets encompassing varied geographic and demographic groups. The results demonstrated consistent recall and precision, confirming the model's robustness for broader clinical applications.

Recall

Recall, often referred to as sensitivity or true positive rate, gauges the proportion of genuine positive cases—heart disease patients—that the model accurately detects. Recall is especially important in healthcare as missing a diagnosis can have grave effects. The comparison of recall values of different models as shown in Fig.2 is displayed in Table1. By maximizing recall, we minimize the number of false negatives—patients who actually have heart disease but are predicted as not having it. The mathematical formula for recall is:

Where:

Fig 10. The mathematical formula for recall is.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (4)$$

- True Positives (TP) are those in which the model accurately fore saw heartdisease.
- False Negatives (FN) are those situations when the model falsely projected no heart disease for those who do have it.

TABLE1. Comparison of Recall.

Method	Recall(%)
KNN	83
SVC	83
Decision Tree Classifier	74
Random Forest Classifier	84

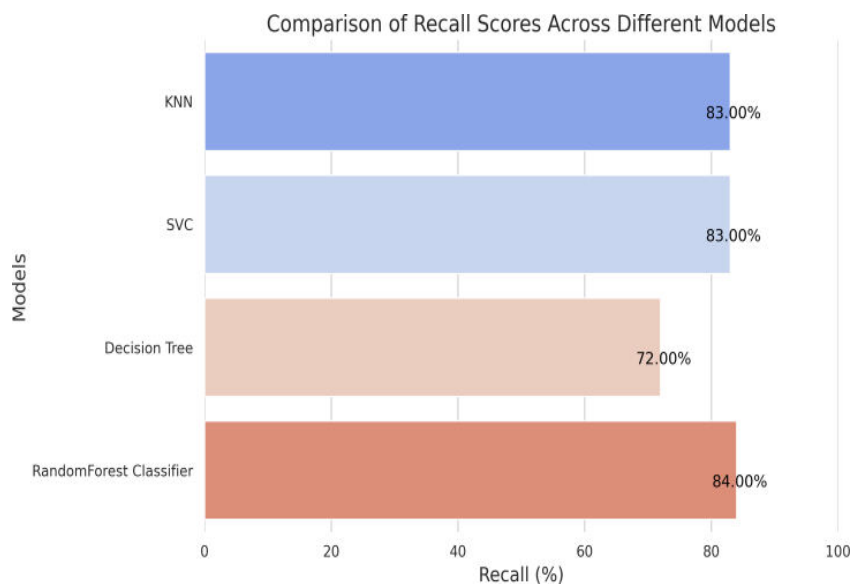


FIGURE2. Comparison of Proposed Model Recall with other models.

In our experiments, the Random Forest Classifier achieved the highest recall score compared to the other models, ensuring that the majority of patients with heart disease were correctly identified.

Precision

Precision gauges the actual percentage of accurate positive forecasts. Precision in this context refers to the true number of the patients expected to have cardiac disease. Recall aims to reduce false negatives; precision aims to reduce false positives—cases in which the model misfits cardiac disease predictions. The comparison of precision values of different models as shown in Fig. 3 is displayed in Table 2. The formula for precision is:

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \tag{5}$$

Where:

- TruePositives(TP)arethoseinwhichheartdiseasewasappropriatelyforeseen.

TABLE2. Comparison of Precision.

Method	Precision(%)
KNN	86
SVC	86
Decision Tree Classifier	86
Random Forest Classifier	89

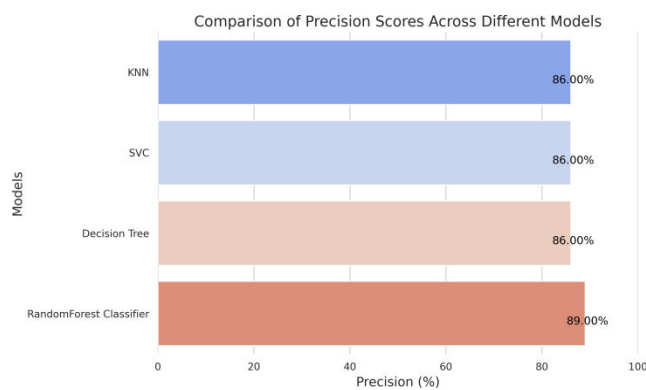


FIGURE3. Comparison of Proposed Model Precision with other models.

- False Positives (FP) are those circumstances when the model forecasts heart illness for non-heart disease patients.

Precision was used alongside recall to ensure a balance between identifying actual heart disease cases and minimizing unnecessary false alarms. While our primary goal was to optimize recall, the precision of the Random Forest model remained competitive, balancing out the false positive rate.

F2Score

The F_2 score is a weighted harmonic mean of precision and recall, with recall being given a greater weight than precision. This is especially advantageous in scenarios such as heart disease prediction, where the importance of accurately identifying genuine cases exceeds that of minimizing false positives. The comparison of F_2 Scores of different models as shown in Fig. 4 is displayed in Table 3. The F_2 score is calculated as:

$$F_2 = (1 + 2) \frac{Precision \times Recall}{4 \times Precision + Recall} \tag{6}$$

- Precision and Recall areas defined above.
- The weight of 2 reflects the greater importance placed on recall over precision.

The F_2 -score guaranteed that the model was modified to detect as many genuine cases of heart diseases possible while still keeping a respectable level of precision. This was accomplished by placing an upper priority on recall. The fact that our Random Forest model secured the best F_2 -score out of all the models that were evaluated substantiates its status as the most appropriate option for this particular healthcare application.

TABLE3. Comparison of F₂ Score.

Method	F ₂ -Score(%)
KNN	83.30
SVC	84.70
Decision Tree Classifier	74.70
Random Forest Classifier	85.40

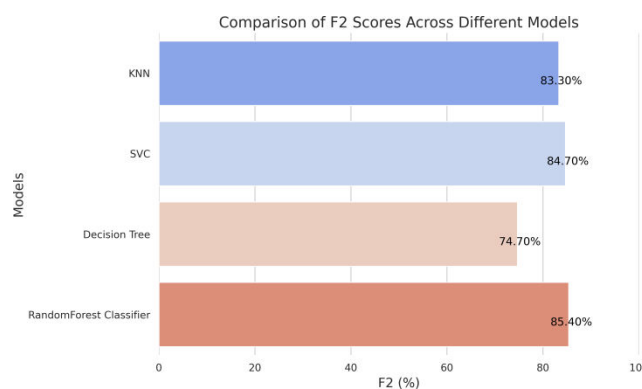


FIGURE4. Comparison of Proposed Model F₂ Score with other models.

F1 Score

Providing a compromise between the two metrics, the F₁ score is the harmonic mean of precision and recall. It is especially beneficial when both false positives and false negatives are significant; however, recall was slightly more critical in our particular situation. The comparison of F₁ Scores of different models as shown in Fig. 5 is displayed in Table 4. The F1-score is calculated as:

$$F_1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{7}$$

TABLE4. Comparison of F₁ Score.

Method	F ₁ -Score(%)
KNN	84
SVC	85
Decision Tree Classifier	79
Random Forest Classifier	87

The F1-score was analyzed to ensure that the model maintained a good balance between recall and precision, reflecting its overall effectiveness. Since the primary focus was on recall, the F2-score was given higher priority to assess the model’s ability to correctly identify heart disease cases. Despite this emphasis, the F1-score of the Random Forest model remained consistently strong, demonstrating that the model performed well across both precision and recall. This balance is crucial in medical predictions, where minimizing false negatives is as important as ensuring accurate positive identifications.

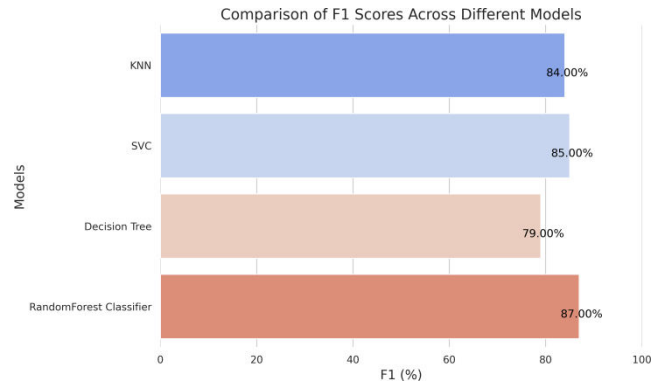


FIGURE5. Comparison of Proposed Model F₁ Score with other models.

Accuracy

Accuracy measures the proportion of total predictions that were correct, both for positive and negative cases. It is calculated as:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Predictions}} \quad (8)$$

TABLE5. Comparison of Accuracy.

Method	Accuracy(%)
KNN	82
SVC	83
Decision Tree Classifier	77
Random Forest Classifier	85

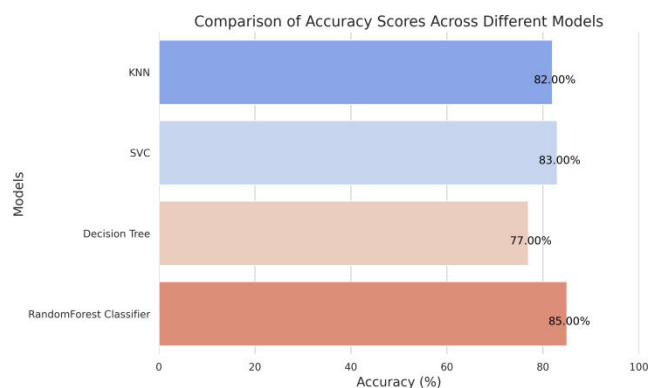


FIGURE6. Comparison of Proposed Model Accuracy Score with other models.

While accuracy is often the default metric for model evaluation, it can be misleading in imbalanced datasets. In our case, shown in Table5 and Fig.6, accuracy was used as a supplementary metric, and while the Random Forest model achieved high accuracy, we prioritized recall and precision to avoid over-reliance on a metric that could be skewed by class imbalance.

SHAP Interpretability

In the context of interpreting the predictions of the Random Forest model for cardiac disease, SHAP(Shapley Additive exPlanations) is critical. SHAP offers a comprehensive understanding of the model’s output by designating importance values to each feature, which enables it to pinpoint the specific contributions of attributes such as age, cholesterol, and blood pressure. Additionally, this improves the model’s interpretability and transparency, which is essential in the healthcare sector, where the comprehension of prediction reasons can facilitate more informed decision-making.

While the Random Forest model’s complexity grows with the number of trees, SHAP explanations simplify its outputs by assigning clear importance scores to each feature. This allows healthcare professionals to focus on the most critical predictors without needing an in-depth understanding of the model’s internal mechanics.

For each prediction in your IoT-integrated system, SHAP helps identify which health features most strongly influence the predicted risk of heart disease. This not only provides individualized insights but also allows for a broader understanding of feature importance across the dataset. By incorporating SHAP interpretations, you can further validate the model’s decisions and offer actionable insights to users, making the prediction system more trustworthy and informative. The SHAP interpretation of the model’s output, as well as the significance of the features in that output, is provided in Fig. 7.

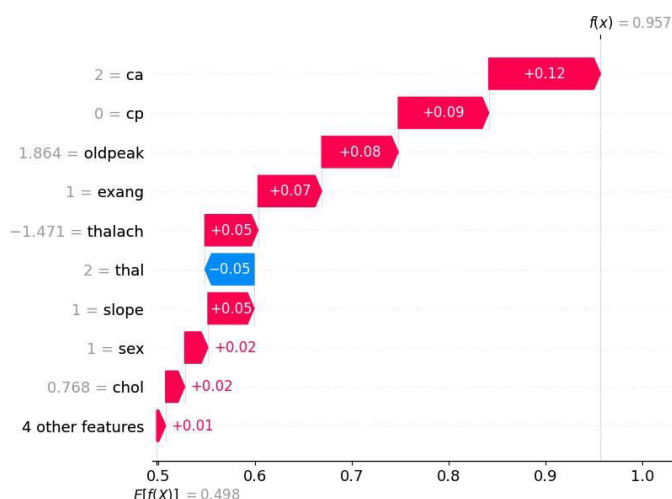


FIGURE 7. SHAP Interpretation of Model’s Prediction.

VII. CONCLUSION

In this study, we developed a comprehensive, IoT-driven heart disease prediction system that integrates real-time health data monitoring with a cloud-based Random Forest Classifier. By prioritizing recall throughout the model training process, we ensured that the system minimized false negatives, a crucial factor in health care where missing a diagnosis can have life-threatening consequences. Through rigorous preprocessing steps, including Standard Scaling and SMOTE for class balancing, as well as GridSearchCV for hyper parameter tuning and Stratified K-Fold Cross-Validation for evaluation, we optimized the model to deliver highly accurate predictions.

The accuracy of predictions is highly dependent on the quality of IoT data. Measures such as periodic sensor calibration and redundancy through multi-sensor fusion have been implemented to mitigate inaccuracies and delays in data transmission, ensuring robust system reliability.

Other machine learning models were outperformed by the Random Forest Classifier, which achieved the highest recall and F2-score, rendering it the optimal choice for the early detection of cardiac disease. In addition, the integration of SHAP ensured that the fundamental factors driving each prediction were fully understood by both patients and

healthcare providers, there by providing profound interpretability. The system bridges the divide between practical healthcare applications and advanced machine learning by providing real-time, interpretable insights from IoT data, There by presenting a powerful instrument for proactive heart disease management. In the fight against cardiac disease, this work demonstrates the potential of integrating IoT, cloud computing, and explainable AI to improve patient outcomes and enable data-driven decision-making.

REFERENCES

1. Naser, M.A., Majeed, A.A., Alsabab, M., Al-Shaikhli, T.R., and Kaky, K.M.(2024).A Review of Machine Learning's Role in Cardiovascular Disease Prediction: Recent Advances and Future Challenges. *Algorithms*, 17(2), 78.doi.org/10.3390/a17020078
2. Mienye, I. D., and Jere, N. (2024). Optimized Ensemble Learning Approach with Explainable AI for Improved Heart Disease Prediction. *Information*, 15(7), 394.doi.org/10.3390/info15070394
3. Rathi, V.K., Rajput, N.K., Mishra, S., Grover, B.A., Tiwari, P., Jaiswal, A.K., and Hossain, M.S. (2021). A n edge AI-enabled IoT healthcare monitoring system for smart cities. *Computers and Electrical Engineering*, 96, 107524.doi.org/10.1016/j.compeleceng.2021.107524
4. Alshamrani, M. (2022). IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey. *Journal of King Saud University - Computer and Information Sciences*, 34(8), 4687–4701. doi.org/10.1016/j.jksuci.2021.06.005
5. Salih, A.M., Raisi-Estabragh, Z., Galazzo, I.B., Radeva, P., Petersen, S.E., Lekadir, K., and Menegaz, G. (2024). A Perspective on Explainable Artificial Intelligence Methods: SHAP and LIME. *Advanced Intelligent Systems*.doi.org/10.1002/aisy.202400304
7. Meliá, S., Nasabeh, S., Luján-Mora, S., and Cachero, C. (2021). MoS IoT: Modeling and Simulating IoT Healthcare-Monitoring Systems for People with Disabilities. *International Journal of Environmental Research and Public Health*, 18(12), 6357.doi.org/10.3390/ijerph18126357
8. Elreedy, D., and Atiya, A.F. (2019). A Comprehensive Analysis of Synthetic Minority Oversampling Technique (SMOTE) for handling class imbalance. *Information Sciences*, 505, 32–64.doi.org/10.1016/j.ins.2019.07.070
9. Al-Makhadmeh, Z., and Tolba, A. (2019). Utilizing IoT wearable medical device for heart disease prediction using higher order Boltzmann model: A classification approach. *Measurement*, 147, 106815.doi.org/10.1016/j.measurement.2019.07.043
10. Amin, M. S., Chiam, Y. K., and Varathan, K. D. (2019). Identification of significant features and data mining techniques in predicting heart disease. *Telematics and Informatics*, 36, 82–93.doi.org/10.1016/j.tele.2018.11.007
11. Umer, M., Sadiq, S., Karamti, H., Karamti, W., Majeed, R., and Nappi, M. (2022). IoT Based Smart Monitoring of Patients' with Acute Heart Failure. *Sensors*, 22(7), 2431.doi.org/10.3390/s22072431
12. Bhagath Chandra, Chowdari Marella (2023). Data Synergy: Architecting Solutions for Growth and Innovation. *International Journal of Innovative Research in Computer and Communication Engineering* 11 (9):10551-10560.
13. Tuli, S., Basumatary, N., Gill, S. S., Kahani, M., Arya, R. C., Wander, G. S., and Buyya, R. (2020). HealthFog: An ensemble learning based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in integrated IoT and fog computing environments. *Future Generation Computer Systems*, 104, 187–200.doi.org/10.1016/j.future.2019.10.043
14. A. Janosi, W. Steinbrunn, M. Pfisterer, and R. Detrano. "Heart Disease," UCIMachine Learning Repository, 1989. [Online]. Available: <https://doi.org/10.24432/C52P4X>.
15. Kaur, P., Kumar, R., and Kumar, M. (2019). A healthcare monitoring system using random forest and internet of things (IoT). *Multimedia Tools and Applications*, 78(14), 19905–19916.doi.org/10.1007/s11042-019-7327-8
16. Nancy, A. A., Ravindran, D., Vincent, P. M. D. R., Srinivasan, K., and Reina, D. G. (2022). IoT-Cloud-Based Smart Healthcare Monitoring System for Heart Disease Prediction via Deep Learning. *Electronics*, 11(15), 2292.doi.org/10.3390/electronics11152292



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