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A Secure Remote Health Monitoring for Heart Disease Prediction Using Machine Learning and Deep Learning Techniques in XAI Framework †

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Abstract: Cardiovascular diseases (CVD) are the most prevalent cause of death worldwide and it has become an important concern for the physicians. Clinical practices have often failed to achieve high accuracy for CVD prediction. Machine learning provides benefits not only for clinical prediction but also for feature ranking, which improves clinical professionals' interpretation of outputs. Explainable Artificial Intelligence (XAI) concept seeks to address the lack of Explainability of machine learning and deep learning models provides healthcare professionals with patient-tailored decision-making tools for improving treatments and diagnostics. This paper aims to predict heart disease using RHMIoT model in XAI framework.

Keywords: machine learning; deep learning; artificial intelligence; IoT; XAI

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1. Introduction

CVDs are the most prevalent cause of morbidity and mortality throughout the world. CVDs enforce significant social and financial costs, including direct costs for diagnostic equipment, treatment by the specialists, as well as indirect costs resulting from decreased quality of life, morbidity and loss of productivity. Furthermore, diagnostic equipment is primarily available in specialized hospitals in large cities. The patients are in leaving small towns are getting lack of such services. Computational methods can assist in identifying high-risk individuals and motivating them to change their behaviors for the purposes of preventive medicine. Based on their risk score outputs, these CVD models are divided into four groups: 1. If-Then models, 2. Formula-based models, 3. Machine learning models and 4. Chart-based models. These models have either accuracy or interoperability limitations [1]. Machine learning (ML) and Deep Learning (DL) are the subfields of Artificial intelligence (AI). ML and AI are emerging technologies that are playing significant roles in healthcare and personalized clinical support. Clinical data in healthcare consists of electronic health data and sensor data from Internet of Things (IoT) devices. The data are available in both unstructured and structured forms. Deriving meaningful and decision-making information by a human is difficult on these data. The IoT and cloud-enabled technologies work together closely to provide medical assistance and maintain the electronic health records of patients. With the help of knowledge-based systems and digital medical devices, AI expert systems can be designed to provide an expert opinion. AI algorithms examine IoT data from smart watches, medicines, wearable monitoring devices, and other sources. The data assists patients, doctors, and pharmaceutical companies in evaluating medical conditions, providing feedback on treatments, medication therapy, patient outcomes, and so on.

In recent years, an additional concept known as Explainability has emerged, called as XAI in some contexts [2]. XAI is a type of AI in which the outcome can be understood by humans. Explainable ML models or interpretable ML models enable medical professionals to make reasonable and data-driven decisions to provide individualized care that may ultimately result in high quality healthcare services. These models are part of the XAI field that defines a set of ML techniques to produce more explainable models while maintaining a high level of learning performance and enable humans to understand, appropriately trust, and effectively manage the emerging generation of artificially intelligent partners [3]. The major challenges in healthcare are model interoperability and data interpretation. Another challenge is distributed, heterogeneous data storage. Medical aid can easily reach people in remote locations and those who only need preliminary medical assistance with the aid of IoT and ML techniques. The aim of this study is to identify cardiac diseases using machine learning and deep learning algorithms using a secured remote health care application.

The aim of the study are listed below

- A RHMIoT system proposed using medical sensors to perform automated analysis, clustering, processing, and finally, visualizes the predicted results.
- The data is transferred to cloud storage using encryption and decryption techniques to prevent unauthorized users accessing.
- The XAI based SHAP and PCA feature selection techniques applied on the dataset for selecting the best features and the performance of the XAI-based method accuracy is evaluated using a variety of evaluation metrics, including accuracy, recall, and precision.

2. Literature Review

Moreno-Sanchez, P. A. et al. [4], discussed about the development of a heart failure survival prediction model using ensemble trees and ML techniques. XGBoost outperformed with 83% accuracy with unseen data, compared to the other ensemble tree options. Feature selection technique is performed to identify the relevant features to produce the model's results. The model's interpretability and fidelity are then quantitatively assessed, resulting in a balanced ratio between these two variables. Dave, D. et al. [5] discussed the usage of XAI techniques over heart disease datasets with the goal of creating trust in medical practitioners. The patient diagnosis outcomes are generated by the black-box model. The goal of XAI is to create an AI system that is understandable, trustworthy, accountable, interpretable, observable, and explainable among other things. Yang, G. et al. [6] conducted a survey on XAI progress and its efficacy in the field of healthcare sector. The authors proposed a XAI solution for a multi-center and multi-model data fusion. Compared to the current model, the previously proposed models are incapable of explaining the decision-making strategy used in categorizing the instances. Hence a model proposed to classify data and can explain about the outcome of the decision. Das, S., et al., [7] focused on dimensionality reduction using XAI to increase the accuracy of heart disease classification. Four SHAP-based explainable ML models were developed for classification, reflecting the feature contributions and calculating the each feature weights to generate the final findings. With the help of dimensional reduction the feature subset was created through FC and FW. Finally the XGBoost classifier outperformed as the best explanation for heart diseases with a 2% increase in model accuracy. Dave, D., et al., [8] proposed an interpretability technique to investigate the heart disease dataset using XAI techniques for deep learning systems. SHAP technique applied to explain the prediction of heart failure on a coronary heart disease dataset, which contains 1562 data items over three years. After screening six machine learning methods, SHAP technique applied to explain the XGBoost model. The performance of the model proved that the mortality rate has dropped over a three-year period. Chen, T., et al., [9] used the LightGBM (Light Gradient Boosting Machine) to predict failure of extubation using the MIMIC-III clinical database. By using the

SHAP method, they carried out the analysis of feature importance and the visualization of key features. All of the models discussed above are insufficient of explaining the decision-making method used in categorizing the cases. It is desired to develop a model that can classify data while explaining the outcome of the decision made.

3. Proposed Methodology

The approaches of this paper are discussed step by step in this section. To improve the capacity of the model, XAI is introduced to increase the effectiveness of AI. Figure 1 depicts the model for predicting cardiovascular disease using the XAI system integration with the ML and DL model in a secured RHMIoT.

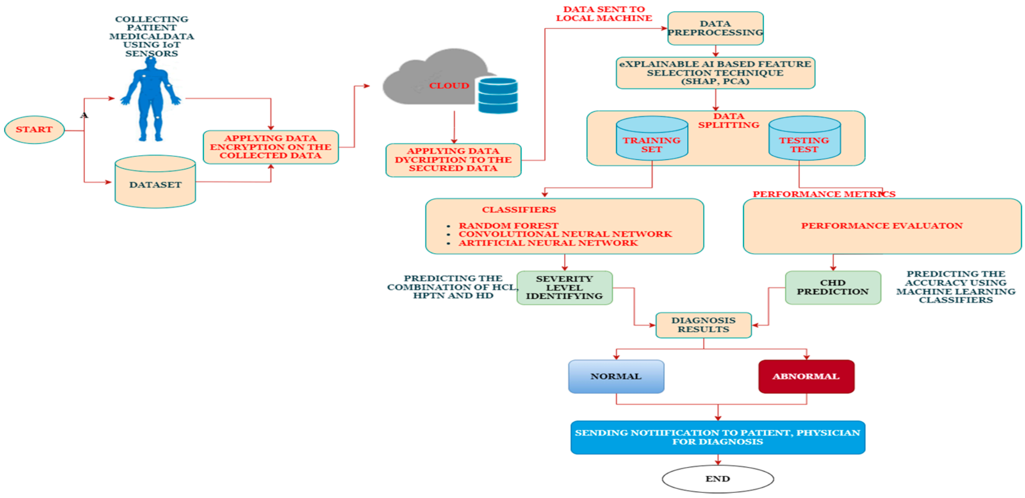

Figure 1. Proposed RHMIoT framework.

The model comprises with a sensor layer, transport layer and an application layer. The sensor layer is used to collect the data using various medical IoT sensors. Using ML-based applications, physicians can continuously analyze their patients' diseases and health status using IoT-medical sensors [10]. After the patient data collected through the sensors, the data is transferred to cloud storage using encryption and decryption techniques to prevent unauthorized users from accessing it. A performance algorithm is used to encrypt sensitive patient data. An algorithm designed for enhancing security with a key-dependent dynamic S-Box and a hyper elliptic curve. In the application layer, heart disease was predicted using ML and deep learning algorithms. The RHMIoT framework is divided into two phases. In phase-1 the patient's risk of HPTN and its severity level is calculated. The DM algorithm is applied to the patient's medical data to calculate HPTN and its severity levels [10]. In phase-2 heart disease accuracy calculated using machine learning and deep learning classifiers. Framingham dataset is used to train our model which is retrieved from Kaggle. The heart disease dataset contains 4238 records with 16 attributes. The data pre-processing carried out using feature selection and classification techniques. After the training process, the IoT medical device sensor data is tested by classifying and contrasting the results. To accurately predict the presence of heart disease, the proposed RHMIoT framework uses Artificial Neural Network (ANN), Convolutional Neural Network (CNN) and Random Forest (RF). The following section provides a detailed explanation of the training procedure.

3.1. Data Preprocessing

Data preprocessing method used to replace missing data or remove noise. The missing values of the dataset are identified and updated by median value of the attribute. A studentized residual technique is used to lower the residuals. It finds the correlation among the features and helps to find the outliers of the given dataset. The preprocessing of data aids in improving heart disease detection. After data pre-processing the dataset is normalized using a min-max normalization technique.

$$\acute{V}_I = \frac{V_I - MIN_A}{MAX_A - MIN_A}\ (NEW\_MAX_A - \ NEW\_MIN_A)\ NEW\_MIN_A \quad (1)$$

3.2. Feature Selection

Explainable AI (XAI)-based feature selection techniques used to identify and select the most relevant features from a dataset while maintaining interpretability and transparency in the feature selection process. These techniques are particularly useful when you need to understand why certain features were chosen or excluded from a predictive model. SHAP (SHapley Additive exPlanations) and PCA (Principal Component Analysis) used for feature selection.

3.2.1. SHAP is an extremely effective XAI approach. It assigns values to prediction characteristics, showing their contributions to the model's output. SHAP allows us to discover the factors that influence AI decisions, making them more interpretable and trustworthy. The following Figure 2 dependence plot shows how a particular characteristic (in this case, 'age') effects the model's output (in this case, the chance of belonging to class 1, which might signify a favorable conclusion in your binary classification problem). The y-axis (SHAP Value) displays the SHAP values for the 'age' characteristic. SHAP values represent the feature's influence on the model's prediction for each data point. Positive SHAP values increase the model's output, whereas negative values decrease it. The x-axis represents the values of your test data's 'age' feature. Each point on the diagram represents one of the test data points. The point's vertical location corresponds to the SHAP value for 'age' for that individual data point. If the trend line is generally flat, it suggests that the 'age' attribute has little to no link with the model's output. In other words, changes in 'age' have no discernible effect on the model's forecast. If the trend line is favorably sloping, it indicates that as 'age' increases, so does the model's prediction (probability of belonging to class 1). According to the concept, this suggests that older people are more likely to belong to class 1. The range supplied between −2.0 to −1.0. The dependence plot's main function is to show how changes in the feature of interest ('age') affect the model's output. The data and SHAP values for a specific dataset and model determine the specific axis values and ranges.

3.2.2. PCA is a technique for reducing dimensionality in data analysis and visualization. Reducing SHAP values can be high-dimensional, especially when features are more in a dataset. It can be difficult to visualize high-dimensional data in a single graph. PCA aids in dimensionality reduction while maintaining as much information as feasible. PCA finds linear combinations of features that capture the most significant variances in the data. These primary components can aid in the discovery of underlying patterns and correlations between features. The Figure 3 shows the PCA visualization of SHAP values. SHAP and PCA can identify features that are most relevant for heart disease prediction in sensor data. The patient's heart condition was determined using training and testing dataset with an 80:20% ratio. The following Research questions address how XAI environment helps for heart disease prediction:

RQ1: How a machine learning model make predictions for a specific data point in an Explainable AI environment, in this case, "patient 0."

Solution: The decision plot in Figure 4 shows the most critical features that influence the model's prediction for "patient 0." The absolute SHAP values of these attributes are ranked from top to bottom. SHAP Factors: Each feature's SHAP values are represented by horizontal bars. Positive SHAP values (on the right) indicate that the feature raises the model's prediction (towards a positive class), whereas negative SHAP values (on the left) reduce the prediction (towards a negative class). In binary classification, the probability threshold (generally 0.5) is what distinguishes the two classes. If the projected value line is to the right of the vertical centerline, the class is predicted to be positive.

RQ2: How effectively does a Random Forest classifier perform in distinguishing between individuals with heart disease and those without, as demonstrated by the confusion matrix heatmap, and what insights can be gained from the distribution of TP, TN, FP, and FN predictions in the context of heart disease classification?

Solution: The confusion matrix heatmap generated using a Random Forest classifier on the heart disease dataset provides valuable insights into the model's performance which is shown in Figure 5. It reveals the distribution of TP, TN, FP, and FN predictions. These metrics are crucial for understanding the classifier's ability to correctly identify individuals with heart disease TP, correctly identify those without heart disease TN, misclassify healthy individuals as having heart disease FP, and misclassify individuals with heart disease as healthy FN.

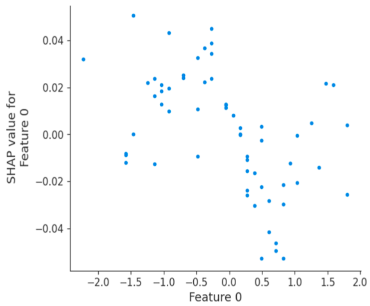

Figure 2. Dependence Plot.

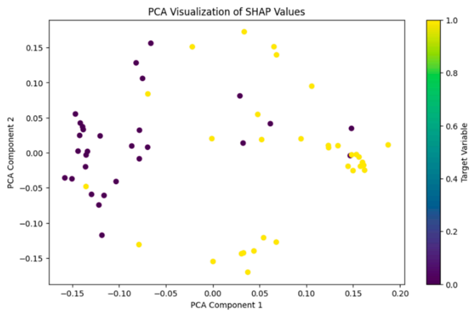

Figure 3. Decision Plot for PCA Visualization.

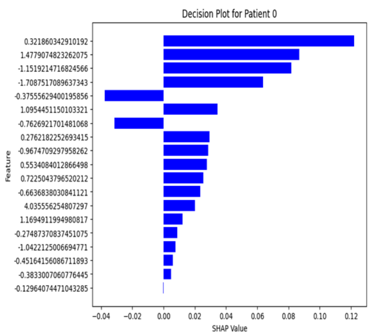

Figure 4. Decision Plot.

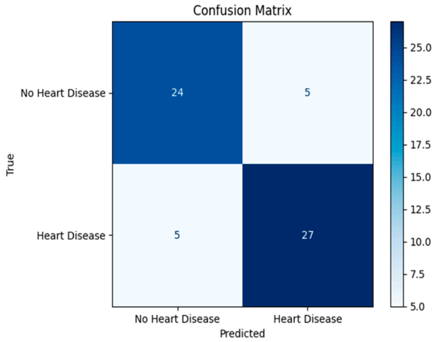

Figure 5. Confusion Matrix.

3.3. Machine Learning Algorithms

The flow of a RHMIoT model begins with the dataset's input parameters. After data preprocessing and feature selection the dataset is passed on to the proposed framework. For comparative analysis RF, ANN and CNN algorithms were used in study.

Random Forest (RF): An AI ensemble method combines several learning algorithms to produce accurate prediction. Compared to a statistical ensemble, a machine-learning ensemble is typically much more flexible in its structure. During the training phase, the RF algorithm constructs multiple decision trees. The RF selects the majority decision of the trees as the final decision. The "forest" is an ensemble of decision trees, which are typically trained through the "bagging" method. Bagging used to combine several learning models to improve the overall result.

3.3.1. Convolutional Neural Network (CNN): CNN has the ability of feature learning. Hence CNN is a suitable algorithm for heart disease prediction at an earlier stage. We can use CNN for binary classification. In Heart disease prediction a patient suffering from CHD is classified as "1" and not-subfreezing classified as "0", which is called a binary classification. CNN architecture operates in a single-input and single-output sequential mode. The CNN architecture relies heavily on the convolution layer for feature extraction.

3.3.2. Artificial neural network (ANN): It is interrelated with input, hidden, and output units. The patient's risk factors are accepted in the input unit for medical diagnosis. ANN has proven to be more effective in the field of healthcare and medicine. In the proposed model 8 neurons constructed for the input layer to correlate with 8 important characteristics. The output class variable generates either 0 or 1, where 0 indicates that the person does not have heart disease and 1 indicates the person suffers with heart disease.

4. Results and Discussion

The aim of this study is to calculate the severity level of heart disease and prediction accuracy. In the proposed RHMIoT model, three different classification algorithms RF, ANN and CNN were applied to a heart disease test dataset.

The Table 1 shows the performance metrics of the proposed classifiers. The performance of each experiment is compared through performance metrics and statistical results. For early diagnosis of heart disease, more attention is given to-wards achieving maximum true positives. The deep learning algorithms were performed well compared to machine learning classifiers in terms of testing accuracy, precision and recall. RF is recognized as the weak classifiers for the proposed work because they demonstrated low accuracy. The Figure 6 shows the plot graph representation of the proposed classifiers.

Table 1. Experimental Results.

Classifier	Accuracy	Precision	Recall
RF	87.69%	89.00%	90.00%
ANN	91.00%	92.00%	93.00%

CNN	88.10%	89.10%	91.00%

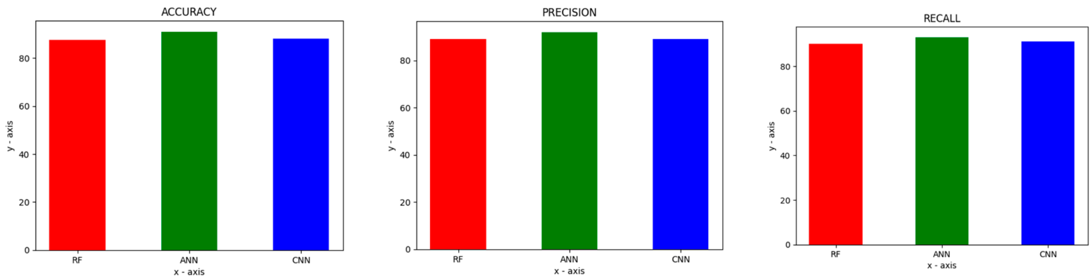

Figure 6. Box Plot Bar Graph for the Accuracy, Precision and Recall.

5. Conclusions

Due to the rapid increase of CVDs, remote health monitoring becomes more popular over the globe. This technique helps patients with diagnoses at home or in a remote area. A lightweight block encryption and decryption technique is provided for a secure RHMIoT. A variety of IoT medical sensors are used to gather data to test the suggested model. XAI based SHAP and PCA techniques were used for feature selection. Heart disease accuracy calculated using various Deep learning and machine learning algorithms. The outcomes were determined using several performance matrices. In comparison to other machine learning and Deep Learning techniques provided the greatest accuracy of 91.00% for ANN. In future we will try to improve the speed and precision of our model by making a few dynamic adjustments in accordance with the requirements of the user.

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