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Heart Attack Prediction uisng Random Forest

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***Abstract*—Cardiovascular illnesses and cardiac arrests, in particular, have become the major cause of death allover the world, highlighting the need to develop new methods for early prediction and diagnosis for better treatment and prevention. The proposed work integrates the application of Random Forests in a predictive ML (ML) model boosted with Explainable Artificial Intelligence (XAI) techniques, to be able to predict if the cardiac arrest could happen or not. The RF model was trained using a clinical database consisting of demographic, social and medical data and was able to predict the chances of a cardiac arrest with an increased level of precision. XAI techniques like SHAP (Shapley additive explanations) and Partial dependency plots (PDP) were utilized to improve the accuracy and the reliability of the model with XAI. Together, these techniques helped to explicate the forecast yielded by the model as to what features were important and what were the predictions that led towards the conclusions in the model. Cholesterol levels, along with blood pressure and age, were among the key indicators scrutinized that supported the functioning of the model. The results presented in the last section highlighted the main risk factors and provided additional relevant information to healthcare providers, which could greatly improve their decision-making and treatment of patients by knowing what treatments to provide to which patients. The investigation addresses the challenge of the medical AI paradigm by overcoming the trade-off between prediction performance and interpretability by developing AI devices that are clinically usable from the use of ML to XAI. The proposed approach enables the prediction of cardiac arrests at an early stage, with the goal of assisting patients and minimizing the costs incurred by the health facilities, by increasing the anticipatory, allowing improved patient care and preventive methods for patients.**

***Index Terms*—Explainable AI, Random Forest, Heart Attack Prediction, SHAP, PDP**

I. Introduction

The analysis of complex medical data has been greatly advanced using predictive models, an area within ML and data science that has demonstrated rapid growth within the medical-care sector [1]. One dominant application of this area using ML models comprises the estimation of cardiac arrest probability, where the concentration is placed on factors which are cholesterol level, age, pressure of blood, and other aspects of lifestyle. In conjunction with standard clinical examination, they will serve as supportive tools for the doctors by providing additional information on the patient's health best suited to those with the high-risk [2]. This research study addresses an improved Random forest [3] model with high classification accuracy by implementing CARTs proving its improvement in predictivity and practical application.

The research demonstrates how interpretability joins predictive accuracy as a vital aspect of the work. Explainable Artificial Intelligence (XAI) techniques [4], [5] and SHAP (Shapley Additive Explanations) [6], [7]. SHAP values make it possible to understand how each feature affects model predictions throughout the forecasting process which enhances judgment transparency. Medical-care providers can understand the model's reasoning through SHAP since it demonstrates how each individual feature affects the final predictive outcome. The model can detect critical risk factors through SHAP evaluation when analyzing patient cardiac arrest possibilities for instance high cholesterol or elevated blood pressure combinations. The investigation of model predictions through SHAP enhances both medical-care provider trust and ensures their confidence while making clinical decisions based on these insights. The incorporation of SHAP into the model delivers benefits which enable physicians to deliver individualized healthcare solutions. Medical-care providers can establish individualized risk-reduction actions when they properly identify the elements that make each patient vulnerable. The specific methods help achieve superior patient results by focusing on the primary risk elements affecting each person.

The use of predictive models in assessing cardiac arrest risk can significantly improve how resources are allocated within medical-care systems. By recognizing persons at high risk early on, medical-care supplier can more effectively direct resources such as specialized tests and preventive measures, leading to enhanced efficiency and reduced costs. Implementing ML for cardiac arrest prediction marks a major advancement in preventive medical-care. By integrating advanced

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predictive capabilities with the interpretability offered by XAI methods like SHAP, this initiative helps to provide a reliable tool with early detection and to personalized treatment for patient care. The strategy boosts of accuracy on cardiac arrest risk assessments and also confirms that the insights gained are accessible and applicable for medical-care personnel, ultimately resulting in improved patient consequences and more efficient medical-care delivery.

II. Literature survey

Recent studies have explored ML techniques for predicting cardiac arrests. Feature selection methods, such as correlation-based and mutual information, enhance the efficiency of the model. Hybrid models which combines the multiple algorithms are showning improved accuracy. Despite favorable results, challenges such as data quality, generalizability of the model, and integration into clinical practices remain. Future research should address these challenges for more effective prediction of heart disease. This study [8] evaluates five machine learning techniques for predicting heart attack risk using patient data, including age, sex, blood pressure, and cholesterol levels. Amidst models that are tested, Support Vector Machine as achieved the best performance.

The research presented in [9] focuses on developing a solution to quickly identify heart disease using ML algorithm in the Jordan University Hospital (JUH) Heart Dataset, employing a hybrid approach that includes particle swarm optimization (PSO), support vector machine (SVM), KNN, random forest. The prediction of coronary artery disease (CAD) using a novel ML approach is proposed in [10], where the authors apply adaptive classification techniques to address the problem of varying medical images containing weak pixels or noise, etc. Another approach for the detection of CAD through heart rate variability (HRV) is proposed in [11], where the authors have used the multiscale wavelet packet transform, K-nearest neighbor entropy, and fuzzy entropy. IN this work, the authors employed the generalized discriminant analysis (GDA) and extreme learning machine (ELM) to detect CAD based on 62 features.

The study of NT-proBNP levels in children with infectious/non-infectious cardiac diseases to identify clinical factors influencing its levels, is presented in [12], in which the application of ML approach to model and analyse the NT-proBNP levels was done on the basis of data collected from 348 participants. This study [13] uses machine learning models to classify cardiovascular diseases using data from the Ain Shams University Coronary Care Unit in Egypt. A comparative analysis of classifiers, including SVM, KNN, and ANN.This [14] researches the application of machine learning algorithms, such as KNN, Logistic Regression, XGBClassifier, and ExtraTreeClassifier, to predict heart attacks, focusing on early detection to lower mortality rates.

A study of several ML based approaches and their comparative analysis is presented in [15]. The authors have considered the Statlog (Heart) data set for the study and observed superior performance of the Support Vector Machine (SVM) with a linearized kernel, paired with the ReliefF feature identification method. The work in [16] addresses volumetric heart segmentation, through 3D visualization using multilevel thresholding and mathematical morphology.

III. Working Model

Random Forest is one of ensemble learning method which builds multiple decision trees and accumulate their results for better accuracy. This model uses bootstrapping, where random subsets of data are sampled with replacement and each tree is trained on a different subset.

To predict cardiac arrests, the first step involves loading the dataset, typically stored in a CSV format (Comma-Separated Values). Using Python's pandas library, the dataset is read into a DataFrame, a two-dimensional labeled structure resembling a table in a database or spreadsheet. For example, a file named 'heart.csv ' could contain medical data of age, cholesterol levels, blood pressure, and a target variable indicating whether an individual experienced a cardiac arrest. Each row represents a person's health information, while columns correspond to specific characteristics (e.g., age or cholesterol). This structured data enables effective analysis and model development.
Pre-processing: The process begins with data collection, where a structured heart attack data set is gathered. The data cleaning is then performed by handling missing values using imputation techniques. Outliers are detected and removed if necessary. Feature scaling is generally not required for tree-based models, but categorical variables must be handled using encoding techniques. Finally, feature selection is applied to remove irrelevant variables, improving model efficiency. This data is then split into training sets and testing sets, generally in 80-20 or in 70-30 ratio, ensuring the model learns from one portion and generalizes well on unseen data.

To begin building a cardiac arrest prediction model, the data set is stacked into a pandas frame for easy manipulation. The target variable, typically labeled as 'output', is separated from the characteristic variables, such as age, cholesterol levels and blood pressure, and stored in y. The features are placed in X. If missing values are found, they are addressed by imputation (e.g., replacing with the mean).

Next, $train\_test\_split$ is employed to divide the data set as two parts: training and testing, in which 80% data from dataset is reserved to train model and the rest 20%of the data is assigned to test model. This helps confirm the model that, it is capable of generalizing the data real-time.

To ensure that the model performs optimally, feature scaling is applied. This procedure is crucial for algorithms which are sensitive to the scale of features of the input. Using the function $StandardScaler$, the characteristics are standardized, transforming them into a set of values that have a zero mean and a unity standard deviation. This normalization helps prevent any single feature from disproportionately influencing the model due to differing magnitudes, leading to more accurate predictions.
Training Random Forest Classifier: To begin preparing Random Forest Classifier, primary step is to initialize the

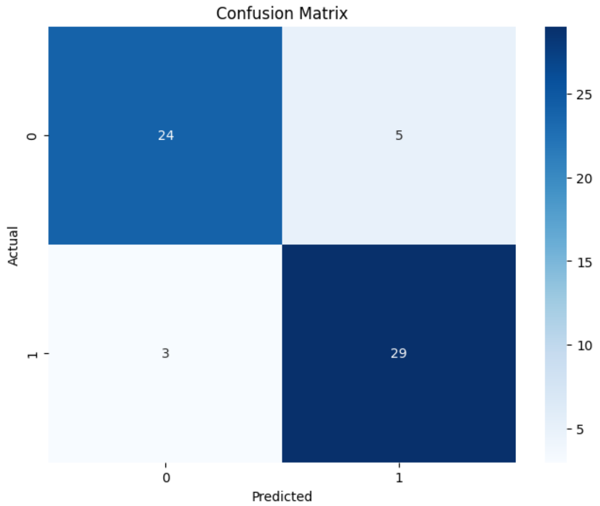

Fig. 1. Confusion matrix for random forest model

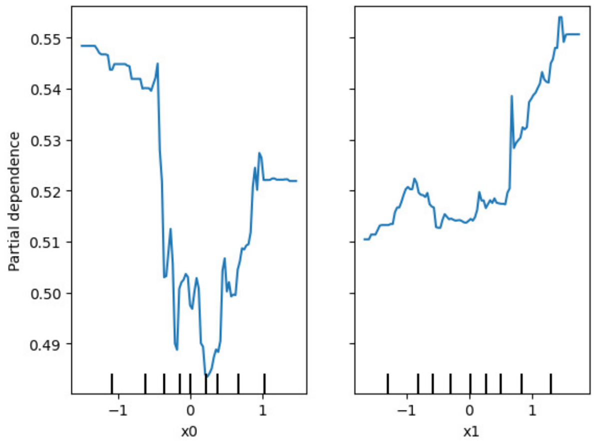

Fig. 2. Partial Dependence Plot

model employing the $RandomForestClassifier$ function. The model is configured with specific hyper parameters, like the trees highest depth (max_depth) and the no. trees ($n\_estimators$). In this case, 100 trees with a maximum depth of 5 are used for simplicity, though these values can be adjusted for better performance. This is followed by the classifier's training in the preprocessed training data set, which includes the standardized features (X_train) and its relevant targets (y_train). The relationship between the input features and the target through the function $fit()$ is learned by the model.

During the training process, the Random Forest algorithm selects data subsets randomly and creates multi-fold decision trees. Each tree makes independent predictions, and the ultimate forecast is determined by aggregating the outcomes from all the created trees, mostly employing popular polling

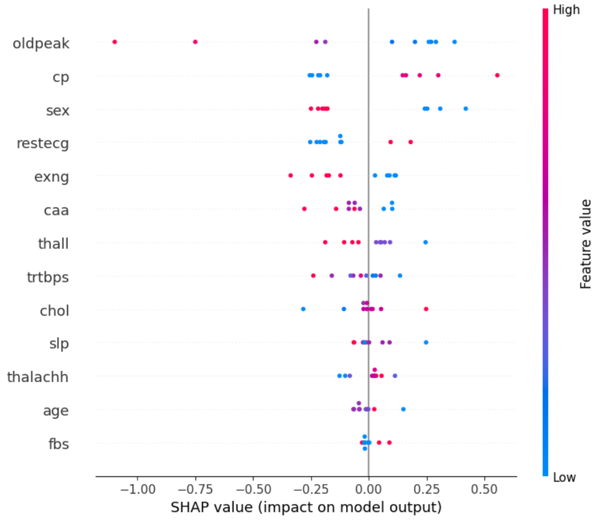

Fig. 3. SHAP Values using XAI

to classify the tasks. The ensemble approach helps improve the robustness and its accuracy by reducing overfitting. Upon successful completion of the training, it is capable of forecasting over the test set and its different metrics, namely, F1 score, accuracy, precision, etc. may be applied to assess its performance. The generalizability of the model is assessed with help of metrics over unseen data, providing information on its effectiveness in predicting cardiac arrests or other outcomes.

For classification problems such as heart disease prediction, precision, precision, recall, F1 score, and ROC-AUC are included in metrics. Accuracy calculates the general correctness, and model's ability to correctly identify positive cases is assessed by precision and recall. The precision and recall ared balanced by F1 score, making it useful in unbalanced data sets. ROC-AUC evaluates the trade-off between sensitivity and specificity.Mean absolute error (MAE), mean squared error (MSE), and R-squared (R^2) metric are used to assess performance For regression tasks. A confusion matrix is often plotted to visualize the classification results.

Evaluating and Interpreting the Model with SHAP: After training the Random Forest Classifier, it is crucial to evaluate its performance to understand how effectively it predicts cardiac arrests. The model is first assessed on test dataset using precision, recall, accuracy, and the F1 score. These metrics produce insights on model's predictive capabilities and its ability to discriminate between the acceptable and rejectable outcomes. Additionally, for visualize model's classification errors, helping to identify areas for improvement, a confusion matrix is used. To further interpret the decision-making process of the model, SHAP (SHapley Additive exPlanations) is employed. SHAP values help explain the percentage of contribution of each feature to the final forecast. For each prediction, SHAP calculates the impact of each feature, providing transparency

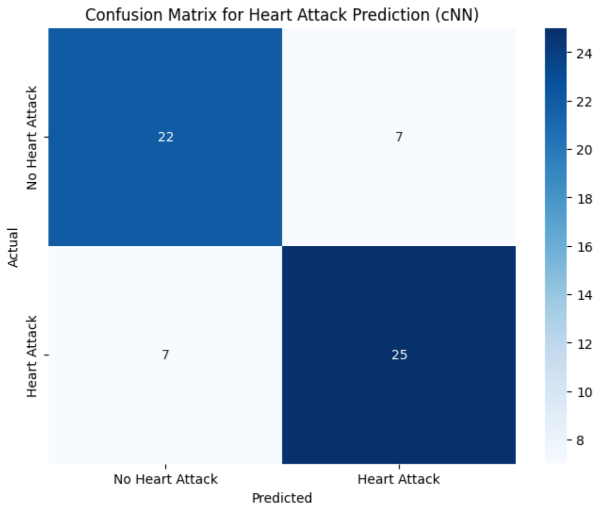

Fig. 4. Confusion matrix of CNN model

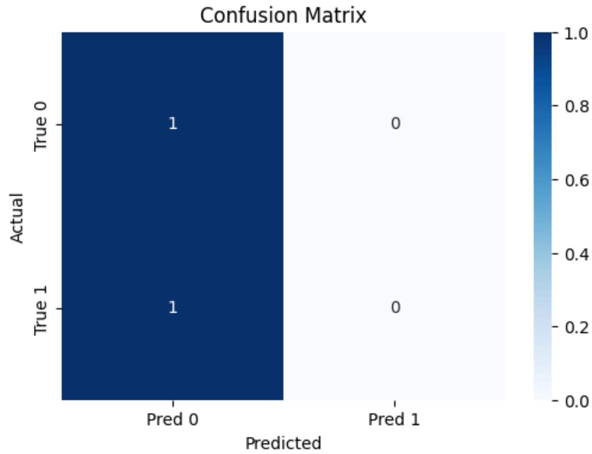

Fig. 5. Confusion matrix of Transformer model

in the model's reasoning.

Explainable AI (XAI) aims to make machine learning models more transparent and interpretable, addressing the black-box nature of complex algorithms like Random Forest. One common XAI technique is feature importance analysis, which measures how significantly each feature contributes to the predictions.

The SHAP values are generated using KernelExplainer, which approximates the output of the model by analyzing the training data. These values are then visualized using summary plots and force plots. A summary plot displays the importance of the features, with colors indicating whether the feature values are high or low. A force plot visualizes contribution of the feature for independent predictions. Using SHAP, valuable information to gained about features driving the predictions, ensuring transparency, and helping to refine the model for better applicability in the real world.

Evaluation of Model and Visualization : The evaluation of Model and visualization is essential to analyze performance and characteristics for a ML model. After training the Random Forest Classifier, its performance is assessed using various metrics. The calculation of metric on the test set and help evaluate how effectively the model distinguishes between cardiac arrest and non-cardiac arrest cases. The confusion matrix, which shows the counts of true positives, true negatives, false positives, and false negatives, gives deeper insights prediction of errors, helping to identify areas where the model may need improvement.

For visualization, a heatmap of a confusion matrix are often used to give a clear visual representation the performance of prediction, with colors indicating the frequency of correct or incorrect classifications. This visualization helps to quickly identify areas where the model is misclassifying instances, offering insights into potential improvements.

Partial Dependence Plots (PDP) help to realize the impact on feature on overall model output. PDPs show how the predicted outcome changes as a feature varies while keeping others constant. PDP visualizes the effect of a single feature on model predictions while averaging other variables. Unlike SHAP, which explains individual predictions, PDP provides global interpretability by showing how the predicted outcome changes as the value of a feature varies.

In addition to performance and evaluation, SHAP (Shapley Additive Explanations) is used for model interpretation. SHAP values measure the contribution of each feature in individual predictions. SHAP summary graphs highlight the most important features in driving the model's predictions, while force graphs provide a detailed view of how specific feature values influence individual predictions. SHAP provides both global and local interpretability, which makes it valuable for understanding complex models.

By combining performance metrics and visualizations, comprehensive understanding is gained on the strengths, weaknesses, and decision-making process of the model, enabling improvements and ensuring transparency.

TABLE I
COMPARISON OF MODEL

Model	Accuracy	Sensitivity	Specificity	precision
Random Forest	86.89%	0.91	0.83	0.85
CNN	73.77%	0.59	0.90	0.80
Transformer	50%	0.00	1.00	0.00

IV. RESULTS AND DISCUSSION

The confusion matrix of the Random Forest trained cardiac arrest prediction model appears in Figure 1. The confusion matrix enables model performance assessment through its comparison of the actual values to predicted values. The matrix offers details about model accuracy and measurement precision and specificity along with recall. The value of TP and

TN indicates correct predictions yet FP and FN values show cases of incorrect classification. The analysis of confusion matrix allows us to improve our model by making necessary changes to decrease errors while maximizing cardiac arrest detection accuracy.

The model trained for cardiac arrest prediction has its partial dependence plot (PDP) shown in Figure 2. The PDP shows how each independent variable (for instance age, cholesterol, blood pressure) affects cardiac arrest risk rates when all other variables remain stable. The PDP explains the outcome change through graphical visualization of feature values alongside predictive probabilities. The graphic reveals how older age together with elevated cholesterol levels make cardiac arrest more likely. Through PDPs the RF model becomes easier to interpret while users can identify important features for better prediction accuracy and model enhancement.

Figure 3 employs XAI (explainable AI) to visualize SHAP values through a chart displaying each datapoint that shows feature SHAP measurements. The SHAP value magnitude stands as the vertical measurement in this axis which reveals how much the feature affects prediction determination. The graphical representation uses blue for lower feature values and red for higher values for representation purposes.The model dedicates more influence to features that display wider spread and appear more often.

The confusion matrix of the CNN-based cardiac arrest predictor appears in Figure 4. The confusion matrix enables performance evaluation of classification models through an analysis between predicted results and actual outcomes. These evaluation values make it possible to determine accuracy together with precision and recall metrics as well as F1 score and specificity values. A diagnostic tool called the confusion matrix pinpoints locations where the model makes errors through incorrect predictions between cardiac arrest and non-cardiac arrest cases so that both model interpretation and optimization can benefit.

Figure 5 shows the confusion matrix for a transformer-based model trained for cardiac arrest prediction. The confusion matrix evaluates the model's performance by displaying four key metrics. True Positives represent the number of positive instances correctly predicted, while True Negatives indicate the negative instances correctly identified. A well-performing model is expected to have a high number of TP and TN, with minimal FP and FN, indicating accurate predictions and effective classification of cardiac arrest cases.

Table I showcase the compares the performance metrics of three different models: Random Forest, CNN, and Transformer. The Random Forest model exhibits the overall highest accuracy of 86.89%, and sensitivity of 0.91, with 0.83 of specificity , and precision of 0.85. On the other hand, the CNN model has an accuracy of 73.77%, with lower sensitivity at 0.59, but higher specificity at 0.90, and a precision of 0.80. Lastly, the Transformer model shows an accuracy of 50%, with zero sensitivity (0.00), perfect specificity at 1.00, and zero precision (0.00). The Random Forest model outperforms the various models across metrics, especially in terms of sensitivity and precision, making it the most reliable among the three for this particular task.

V. Conclusion

The Random Forest model demonstrated strong performance in predicting cardiac arrests, achieving high accuracy and effectively distinguishing between cardiac arrest and non-cardiac arrest cases. The main metrics, such as accuracy, recall, F1 score, and specificity, highlight the robustness of the model, particularly its ability to correctly identify cardiac arrest cases. The significance analysis identified age and cholesterol levels as significant predictors, aligning with existing medical research. Although the model performed well overall, some misclassifications were observed, indicating possible areas for advancement.

By predicting the condition of the patient using these model it becomes easy to identify the severity of the problem and helps to come up with suitable healthcare plan with respective to the patient. This can boost the hospital's capacity to treat patient and healthcare plans and help to efficiently treat the patients.

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