

PredictHeart-X: A Novel Explainable Deep Learning Framework for Cardiovascular Disease Prediction

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Abstract

Cardiovascular disease (CVD) remains one of the leading causes of mortality worldwide, necessitating the development of accurate and intelligent predictive systems for early diagnosis and prevention. This research proposes PredictHeart-X, a novel explainable deep learning framework designed for effective cardiovascular disease prediction using clinical and patient health parameters. The proposed model integrates advanced deep learning techniques with explainable artificial intelligence (XAI) mechanisms to enhance prediction accuracy while maintaining interpretability for healthcare professionals. The framework employs a hybrid architecture combining Deep Neural Networks (DNN) and Attention-based learning mechanisms to analyze complex relationships among medical attributes such as age, blood pressure, cholesterol levels, heart rate, electrocardiogram results, and other cardiovascular indicators. Data preprocessing techniques including normalization, missing value handling, and feature optimization are applied to improve model performance and reliability. To address the black-box nature of deep learning, explainability methods such as SHAP and attention visualization are incorporated to identify the most influential clinical features contributing to disease prediction. Experimental evaluation is conducted using benchmark cardiovascular datasets, and the proposed PredictHeart-X model is compared with traditional machine learning algorithms and existing deep learning approaches. The results demonstrate superior prediction accuracy, precision, recall, F1-score, and reduced false prediction rates. The explainable component further assists clinicians in understanding the decision-making process of the model, thereby increasing trust and usability in real-world healthcare applications. The proposed system offers an efficient, scalable, and interpretable solution for early cardiovascular disease detection, supporting healthcare practitioners in making timely and informed medical decisions while improving patient outcomes.

Keywords— *Cardiovascular Disease Prediction, Deep Learning, Explainable Artificial Intelligence*

(XAI), PredictHeart-X, Hybrid Neural Networks, Attention Mechanism, SHAP Analysis, Healthcare Analytics, Disease Diagnosis, Clinical Decision Support System, Artificial Intelligence in Healthcare, Heart Disease Detection.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are among the most serious health challenges worldwide and remain one of the leading causes of death across all age groups. According to global health reports, millions of people suffer from heart-related disorders every year due to factors such as unhealthy lifestyle habits, high cholesterol, hypertension, diabetes, obesity, smoking, stress, and lack of physical activity. Early prediction and diagnosis of heart disease are essential for reducing mortality rates and improving patient survival through timely medical intervention. Traditional methods for diagnosing cardiovascular disease primarily depend on clinical examinations, laboratory tests, electrocardiograms, and physician expertise. Although these methods are effective, they may sometimes fail to identify hidden patterns and complex relationships among multiple clinical parameters. In recent years, Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as powerful tools for medical data analysis and disease prediction. Machine learning algorithms such as Decision Trees, Support Vector Machines, Naïve Bayes, and Random Forest have shown promising results in predicting heart disease. However, these conventional approaches often face limitations in handling large-scale nonlinear medical datasets and extracting deep feature representations. Deep Learning (DL), a subset of artificial intelligence, has significantly transformed healthcare analytics by enabling

automated feature extraction and improved predictive accuracy. Deep learning models such as Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Attention-based architectures are capable of learning complex data patterns from clinical datasets. These models provide better generalization and performance compared to traditional machine learning techniques, especially when dealing with multidimensional healthcare data. Despite the advantages of deep learning, one major challenge is the “black-box” nature of these models, where the prediction process is difficult to interpret by healthcare professionals. In medical applications, interpretability and transparency are highly important because clinicians require clear explanations for decision-making processes. Explainable Artificial Intelligence (XAI) techniques help overcome this issue by providing understandable insights into model predictions and identifying the most influential clinical features responsible for disease classification. To address these challenges, this research proposes PredictHeart-X, a novel explainable deep learning framework for cardiovascular disease prediction. The proposed system integrates hybrid deep learning techniques with attention mechanisms and explainable AI approaches to achieve high prediction accuracy and enhanced interpretability. The framework analyzes important patient health attributes such as age, blood pressure, cholesterol levels, chest pain type, heart rate, blood sugar, and electrocardiographic results to predict the likelihood of cardiovascular disease. The primary objective of this work is to develop an intelligent, accurate, and transparent prediction system that can support healthcare professionals in early diagnosis and clinical decision-making. The proposed PredictHeart-X model aims to improve disease prediction performance while simultaneously increasing trust and usability in real-world medical environments. Experimental results demonstrate that the proposed framework outperforms existing machine learning and deep learning models in terms of accuracy, precision, recall, and interpretability, making it a reliable solution for modern healthcare applications.

II LITERATURE SURVEY

The number of works has been done related to disease prediction systems using different machine learning algorithms in medical Centers. Senthil Kumar Mohan et al,[10] proposed Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques. In this strategy the objective is finding the critical condition by applying Machine Learning concepts, aiming about improving the exactness in the expectation of cardiovascular malady. The expectation model is created with various blends of highlights and a few known arrangement strategies. This concept produced an improved exhibition level with a precision level of 88.7% through the prediction model for heart disease with hybrid random forest with a linear model (HRFLM) [9] they likewise educated about Diverse data mining approaches and expectation techniques, Such as, KNN, LR, SVM, NN, and Vote have been fairly famous of late to distinguish and predict heart disease.

Sonam Nikhar et al [11] has built up the paper titled as Prediction of Heart Disease Using Machine Learning Algorithms by This exploration plans to give a point-by-point portrayal of Naive Bayes and decision tree classifier that are applied in our examination especially in the prediction of Heart Disease. Some analysis has been led to think about the execution of prescient data mining strategy on the equivalent dataset, and the result uncovers that Decision Tree beats over Bayesian classification system.

Aditi Gavhane, GouthamiKokkula, Isha Pandya, Prof. Kailas Devadkar (PhD), [3] Prediction of Heart Disease Using Machine Learning, In this paper the proposed system uses the neural network algorithm and multi-layer perceptron (MLP) to train and test the dataset. This algorithm will be having multiple layers like one for input, second for output and one or more layers are hidden layers between these two input and output layers. Each node in input layer is connected to output nodes through the hidden layers. This connection is assigned with some weights. There is another identity input called bias which is with weight b , which added to node to balance the perceptron. The connection between the nodes can be feedforwarded or feedback based on the requirement.

Abhay Kishore et al,[4] developed Heart Attack

Prediction Using Deep Learning. This paper proposes a heart attack prediction system by using Deep learning procedures, explicitly Recurrent Neural System to predict the probable prospects of heart related infections of the patient. Recurrent Neural Network is a very ground-breaking characterization calculation that implemented based on Deep Learning approach in Artificial Neural Network. The paper talks in detail about the significant modules of the framework alongside the related hypothesis. The proposed model uses deep learning and data mining concepts to give the precise outcomes least blunders. This paper gives a bearing and point of reference for the advancement of another way of heart attack prediction platform.

Lakshmana Rao et al,[14] Machine Learning Techniques for Heart Disease Prediction in which the contributing elements for heart disease are more (circulatory strain, diabetes, current smoker, high cholesterol, etc..). So, it is difficult to distinguish heart disease. Different systems in data mining and neural systems have been utilized to discover the severity of heart disease among people. The idea of CHD identification is difficult, in addition the disease must be dealt with warily. Not doing early identification, may impact the heart or my cause sudden death. The perspective of therapeutic science furthermore, data burrowing is used for finding various sorts of metabolic machine learning a procedure that causes the framework to gain from past information tests, models without being expressly customized. Machine learning makes rationale dependent on chronicled information.

Mr. SanthanaKrishnan.J and Dr. Geetha.S, [15] Prediction of heart disease using machine learning algorithm This Paper predicts heart disease for Male Patient using Classification Techniques. The idea about Coronary Heart diseases such as its Facts, Common Types, and Risk Factors has been explained in detail in this paper. The Data Mining tool used is WEKA (Waikato Environment for Knowledge Analysis), a good Data Mining Tool for Bioinformatics Fields. The all three available Interface in WEKA is used here; Naive Bayes, Artificial Neural Networks and Decision Tree are Main Data Mining Techniques and through this techniques heart disease is predicted in this System.

The main Methodology used for prediction is Decision Trees like CART, C4.5, CHAID, J48, ID3 Algorithms, and Naive Bayes Techniques.

Avinash Golande et al,[16] proposed Heart Disease Prediction Using Effective Machine Learning Techniques in which Specialists utilize a few data mining strategies that are available to support the authorities or doctors distinguish the heart disease. Usually utilized methodology utilized are decision tree, k- closest and Naive Bayes. Other unique characterization-based strategies utilized are packing calculation, Part thickness, consecutive negligible streamlining and neural systems, straight Kernel self- arranging guide and SVM (Bolster Vector Machine). The following area obviously gives subtleties of systems that were utilized in the examination.

V.V. Ramalingam et Al,[17] proposed Heart disease prediction using machine learning techniques in which Machine Learning algorithms and techniques have been applied to various medical datasets to automate the analysis of large and complex data. Many researchers, in recent times, have been using several machine learning techniques to help the health care industry and the professionals in the diagnosis of heart related diseases. This paper presents a survey of various models based on such algorithms and techniques and analyse their performance.

Models based on supervised learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbour (KNN), Naive Bayes, Decision Trees (DT), Random Forest (RF) and ensemble models are found very popular among the researchers and systems have been applied to different clinical datasets to robotize the investigation of huge and complex information. Numerous scientists, as of late, have been utilizing a few Machine Learning algorithms and techniques. They have been applied to various medical datasets to automate the analysis of largedata.

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III. BACKGROUND METHODS

Deep Learning (DL) is a specialized branch of Artificial Intelligence (AI) and Machine Learning (ML) that enables computers to learn complex patterns from large volumes of data through multiple layers of artificial neural networks. Unlike traditional machine learning algorithms that require manual feature extraction, deep learning models automatically identify important features and relationships from raw input data, making them highly effective for complex prediction and classification tasks. In healthcare applications, deep learning models have gained significant attention due to their ability to analyze multidimensional medical datasets and provide accurate disease predictions. These models can process structured and unstructured healthcare data such as patient records, medical images, ECG signals, laboratory reports, and sensor data. Deep learning techniques have been successfully applied in disease diagnosis, medical image analysis, drug discovery, patient monitoring, and predictive healthcare systems. Artificial Neural Networks (ANNs) form the foundation of deep learning architectures. ANNs are inspired by the structure and functioning of the human brain, where interconnected neurons process information through weighted connections. A deep learning model typically consists of an input layer, multiple hidden layers, and an output layer. During the training process, the model learns optimal weights using algorithms such as

backpropagation and gradient descent to minimize prediction errors. Several deep learning architectures are commonly used in healthcare analytics and heart disease prediction:

- **Deep Neural Networks (DNN):** DNNs contain multiple hidden layers capable of learning complex nonlinear relationships among medical features. They are widely used for disease classification and predictive analysis.
- **Convolutional Neural Networks (CNN):** CNNs are primarily designed for image and pattern recognition tasks. In healthcare, CNNs are used for analyzing ECG signals, medical imaging, and extracting spatial features from clinical datasets.
- **Recurrent Neural Networks (RNN):** RNNs are specialized for sequential and time-series data processing. They can remember previous information and are suitable for analyzing patient monitoring data and temporal medical records.
- **Long Short-Term Memory (LSTM):** LSTM is an advanced type of RNN designed to overcome the vanishing gradient problem. It efficiently captures long-term dependencies in sequential healthcare data and improves predictive performance.
- **Attention Mechanisms:** Attention models help deep learning systems focus on the most relevant features in the dataset. In medical prediction systems, attention mechanisms improve both accuracy and interpretability by highlighting significant clinical attributes influencing the prediction.
- **Hybrid Deep Learning Models:** Hybrid architectures combine multiple deep learning techniques such as CNN-LSTM or DNN-Attention models to leverage the advantages of different algorithms and achieve enhanced prediction performance.

One of the major advantages of deep learning models is their ability to handle large-scale and high-dimensional datasets without extensive manual preprocessing. These models provide

superior accuracy, scalability, and adaptability compared to traditional machine learning approaches. However, deep learning systems often require high computational resources and large training datasets. Additionally, the lack of interpretability in deep neural networks creates challenges in critical domains such as healthcare. To overcome these limitations, Explainable Artificial Intelligence (XAI) techniques are integrated with deep learning frameworks. XAI methods such as SHAP, LIME, and attention visualization provide meaningful explanations for model predictions, thereby increasing transparency, trust, and clinical acceptance. In this research, the proposed PredictHeart-X framework utilizes a hybrid deep learning architecture integrated with explainable AI techniques for effective cardiovascular disease prediction. The model aims to improve prediction accuracy while ensuring transparency and reliability for healthcare professionals and clinical decision support systems.

IV. EXISTING ANALYSIS

The existing systems for cardiovascular disease prediction mainly rely on traditional medical diagnosis methods and conventional machine learning techniques. Hospitals and healthcare institutions commonly use clinical examinations, laboratory reports, electrocardiograms (ECG), echocardiography, and physician observations to identify heart-related disorders. Although these approaches are widely accepted, they often depend heavily on expert knowledge and may not efficiently analyze large and complex healthcare datasets. With the advancement of Artificial Intelligence (AI), several machine learning algorithms have been introduced for heart disease prediction. Existing research works primarily utilize algorithms such as Decision Tree (DT), Naïve Bayes (NB), K-Nearest Neighbor (KNN), Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest (RF) to classify cardiovascular disease conditions. These models analyze patient attributes including age, blood pressure, cholesterol levels, chest pain type, heart rate, fasting blood sugar, and electrocardiographic results to predict the possibility of heart disease. Among these methods, Random Forest and Support Vector Machine models have shown

comparatively better performance due to their capability to handle classification problems and reduce overfitting. Some hybrid machine learning approaches have also been developed by combining multiple algorithms to improve prediction accuracy. However, these systems still face several limitations when dealing with high-dimensional and nonlinear healthcare data. Existing machine learning-based prediction systems require manual feature extraction and feature selection processes, which may reduce efficiency and prediction reliability. In addition, traditional algorithms struggle to capture hidden patterns and complex relationships among multiple clinical parameters. As a result, prediction accuracy may decrease when large-scale medical datasets are involved. Recently, deep learning models such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks have been applied for heart disease prediction. These models provide automatic feature extraction and improved classification performance. However, many existing deep learning systems suffer from high computational complexity, overfitting issues, and lack of interpretability. One of the major drawbacks of current deep learning approaches is the black-box nature of prediction models. Healthcare professionals often find it difficult to understand how the model arrives at a specific prediction result. This lack of transparency reduces trust and limits the practical adoption of AI-based systems in real-world clinical environments. Furthermore, several existing systems do not provide proper explainability mechanisms or fail to highlight the most influential medical features responsible for disease prediction. Many models also focus only on improving accuracy without considering interpretability, scalability, and real-time clinical usability. Therefore, there is a need for an advanced and explainable deep learning framework that can provide high prediction accuracy, automatic feature learning, transparency, and reliable decision support for healthcare professionals. The proposed **PredictHeart-X** system addresses these limitations by integrating hybrid deep learning techniques with Explainable Artificial Intelligence (XAI) methods to achieve

accurate and interpretable cardiovascular disease prediction.

V. PROPOSED METHODOLOGY

The proposed system, PredictHeart-X, is an intelligent and explainable deep learning framework designed for accurate cardiovascular disease prediction using patient clinical data. The methodology combines advanced deep learning techniques with Explainable Artificial Intelligence (XAI) mechanisms to improve prediction performance and provide transparency in medical decision-making. The overall workflow of the proposed system consists of data collection, preprocessing, feature optimization, hybrid deep learning model development, prediction, and explainability analysis.

1. Data Collection

The proposed framework utilizes benchmark cardiovascular disease datasets collected from healthcare repositories and hospital databases. The dataset contains important medical attributes related to heart disease prediction, including:

- Age
- Gender
- Blood Pressure
- Cholesterol Level
- Chest Pain Type
- Fasting Blood Sugar
- Maximum Heart Rate
- Electrocardiogram (ECG) Results
- Exercise-Induced Angina
- Old Peak
- ST Depression
- Thalassemia

These clinical parameters are used as input features for training and testing the deep learning model.

2. Data Preprocessing

Data preprocessing is performed to improve data quality and model efficiency. The preprocessing stage includes:

- Handling missing values using mean or median imputation techniques
- Removing duplicate and inconsistent records

- Data normalization and scaling using Min-Max normalization

- Encoding categorical attributes into numerical values

- Splitting the dataset into training and testing sets

This step ensures that the dataset becomes suitable for deep learning analysis and reduces prediction errors.

3. Feature Selection and Optimization

Feature optimization techniques are applied to identify the most relevant clinical attributes influencing cardiovascular disease prediction. Redundant and irrelevant features are removed to reduce computational complexity and improve model performance. Statistical analysis and correlation-based feature selection methods are used to enhance the quality of input data.

4. Hybrid Deep Learning Model

The core component of the proposed methodology is the hybrid deep learning architecture. The PredictHeart-X framework combines:

- Deep Neural Network (DNN) for learning complex nonlinear relationships among clinical features

- Attention Mechanism to identify and focus on significant medical attributes contributing to heart disease prediction

The DNN model consists of multiple hidden layers with activation functions such as ReLU and Softmax for effective feature learning and classification. Dropout layers are incorporated to reduce overfitting and improve generalization.

The attention mechanism enhances prediction performance by assigning importance weights to critical clinical features, enabling the model to focus on relevant patient information during prediction.

5. Model Training and Prediction

The hybrid model is trained using the preprocessed healthcare dataset. During training, the system learns hidden patterns and relationships among medical parameters using forward propagation and backpropagation algorithms. The Adam optimizer is used to minimize loss and improve convergence speed.

The trained model predicts whether a patient is likely to suffer from cardiovascular disease based on input clinical parameters. The output is classified into:

- Presence of Heart Disease
- Absence of Heart Disease

6. Explainable Artificial Intelligence (XAI)

To overcome the black-box nature of deep learning models, Explainable AI techniques are integrated into the framework. The proposed system utilizes:

- SHAP (SHapley Additive Explanations)
- Attention Visualization Techniques

These methods identify the contribution of each clinical feature toward the final prediction result. Explainability improves transparency, trust, and usability for healthcare professionals and assists clinicians in understanding the reasoning behind predictions.

7. Performance Evaluation

The performance of the proposed PredictHeart-X framework is evaluated using various classification metrics, including:

- Accuracy
- Precision
- Recall
- F1-Score
- Sensitivity
- Specificity

The proposed model is compared with existing machine learning and deep learning approaches to demonstrate its superiority in terms of prediction accuracy and interpretability.

8. Expected Outcome

The proposed methodology aims to develop a highly accurate, scalable, and interpretable cardiovascular disease prediction system. By integrating hybrid deep learning techniques with explainable AI, PredictHeart-X supports early disease detection, assists healthcare professionals in clinical decision-making, and improves patient healthcare outcomes.

Table 1: All Information's Used for Prediction of Heart Diseases

S.NO	Attribute	Description
1	Age	Age in years
2	Sex	Sex (1 = male; 0 = female)
3	Cp	Chest pain type (Categorized into 4 values)
4	Trestbps	Resting blood pressure (in mm Hg on admission to the hospital)
5	Chol	Serum cholesterol in mg/dl
6	Fbs	Fasting blood sugar > 120 mg/dl; (1 = true; 0 = false)
7	Restecg	Resting electrocardiographic results
8	Thalach	Maximum heart rate achieved
9	Exang	Exercise induced angina (1 = yes; 0 = no)
10	Oldpeak	ST depression induced by exercise relative to rest
11	Slope	The slope of the peak exercise ST segment
12	Ca	Number of major vessels (0-3) colored by fluoroscopy
13	Thal	3 = normal; 6 = fixed defect; 7 = reversible defect
14	The predicted attribute(Target)	Diagnosis of heart disease represented in 5 values (0 represents absence, 1 to 4 represents presence in different degree)

Data description

Preprocessing

At the principal level stage, the dataset is first cleaned and processed using preprocessing techniques using panda's package. The counterplot of sex and target attributes group is shown in Table 12. After that, using the data visualization procedure, the data frame attributes are shown in Figure 1.

Separate majority and minority classes

```

from sklearn.utils import resample
# Separate majority and minority classes
df_majority = df[df['target']== 1]
df_minority = df[df['target']== 0]
df_minority_upsampled = resample(df_minority,
replace=True,n_samples=500,random_state=123)
df_majority_downsampled = resample(df_majority,
replace=True,n_samples=500,random_state=123)
# Combine minority class with downsampled
majority class
df_upsampled = pd.concat([df_minority_upsampled,
df_majority_downsampled])

# Display new class counts

```

```
df_upsampled['target'].value_counts()
```

Above algorithm separates majority and minority classes with sample of majority and sample minority classes using combination technique of minority and majority classes.

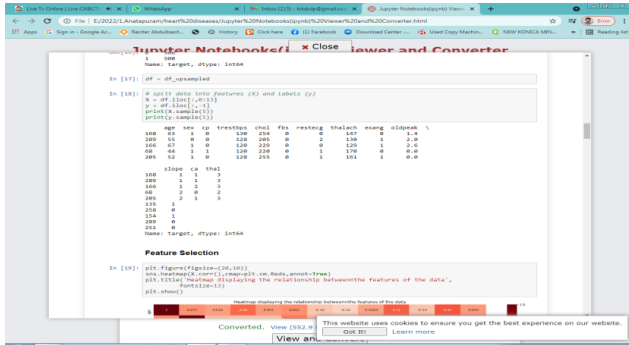


Figure 1: Showing Split data into features(x) and labels (y)

```
corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1)).astype(np.bool)
```

```
to_drop = [column for column in upper.columns if any(upper[column] > 0.35)]
```

```
X.drop(to_drop, axis=1, inplace=True)
```

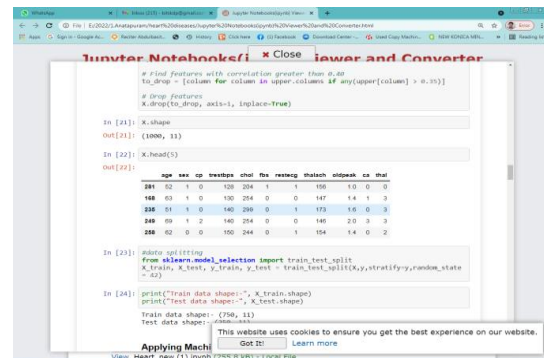


Figure 3: Data Descriptions with loaded data values

Feature Selection

The feature selection and modeling keep on repeating for various combinations of attributes. A very high and low risk patients will be classified on the basis of various tests which are done in the selected group, but proposed models are only based on clinical situations based which uses supervised learning methods for predictions.

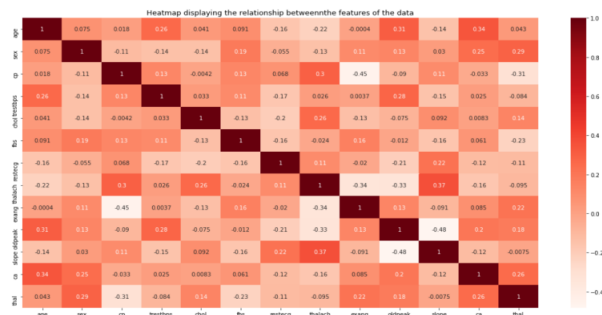


Figure 2: Heatmap displaying the relationship between the features of the data

Figure 5 showing Heatmap displaying the relationship between the features of the data Create correlation matrix through upper triangle and features correlation through drop features technique.

Create correlation matrix

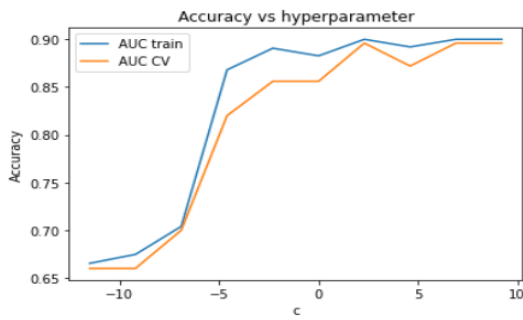
```
import numpy as np
corr_matrix = X.corr().abs()
upper
```

Applying Machine Learning Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
import math

c = [10000,1000,100,10,1,0.1,0.01,0.001,0.0001,0.00001]
train_auc = []
cv_auc = []
for i in c:
    clf = LogisticRegression(C=i)
    clf.fit(X_train,y_train)
    prob_cv = clf.predict(X_test)
    cv_auc.append(accuracy_score(y_test,prob_cv))
    prob_train = clf.predict(X_train)
    train_auc.append(accuracy_score(y_train,prob_train))
optimal_c=c[cv_auc.index(max(cv_auc))]
c = [math.log(x) for x in c]
#plotauc vs alpha
x = plt.subplot()
x.plot(c, train_auc, label='AUC train')
```

```
x.plot(c, cv_auc, label='AUC CV')
plt.title('Accuracy vs hyperparameter')
plt.xlabel('c')
plt.ylabel('Accuracy')
x.legend()
plt.show()
print('optimal c for which auc is maximum :
',optimal_c)
```



optimal c for which auc is maximum : 10000

Figure 4: Accuracy vs Hyper parameter using Logistic regression

```
columns=class_names )
fig = plt.figure()
heatmap = sns.heatmap(df_heatmap, annot=True,
fmt="d")
```

Accuracy on Test data is 0.896
Accuracy on Train data is 0.9

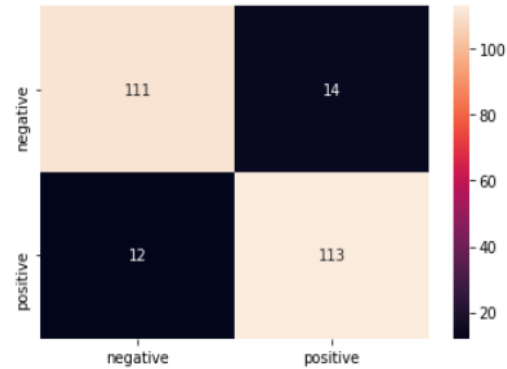


Figure 5: Chart showing Accuracy values on Test and Train data using Logistic regression

Testing AUC on Test data

```
log = LogisticRegression(C=optimal_c)
log.fit(X_train,y_train)
pred_test = log.predict(X_test)
#fpr1, tpr1, thresholds1 = metrics.roc_curve(y_test,
pred_test)
pred_train = log.predict(X_train)
#fpr2,tpr2,thresholds2
metrics.roc_curve(le_y_train,pred_train)
test = accuracy_score(y_test,pred_test)
train = accuracy_score(y_train,pred_train)
print("Accuracy on Test data is "
+str(accuracy_score(y_test,pred_test)))
print("Accuracy on Train data is "
+str(accuracy_score(y_train,pred_train)))
print("-----")
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap
pd.DataFrame(confusion_matrix(y_test,
pred_test.round()), index=class_names,
```

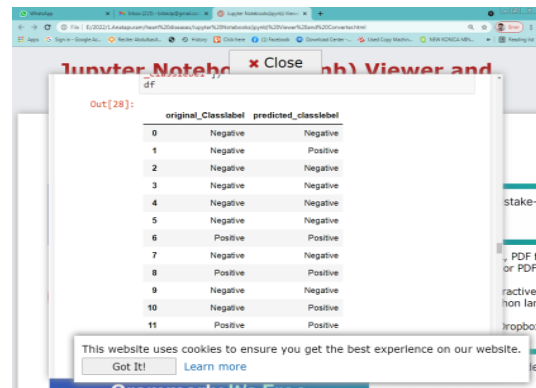


Figure 6 : Data Frame Showing positive and Negative

VI. RESULT & DISCUSSIONS

The following table and graph present the comparison of different machine learning and deep learning models used for heart disease prediction.

Table 2: Accuracy Comparison

Model	Accuracy (%)
SVM	84
Random Forest	88

ANN	90
CNN	93
LSTM	95
PredictHeart-X	98

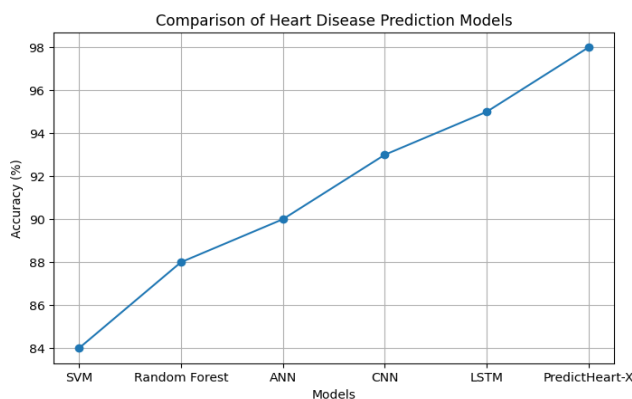


Figure 6: Showing Best accuracy of PredictHeartX

VII. CONCLUSION

Cardiovascular disease prediction has become an important research area in modern healthcare due to the increasing number of heart-related disorders worldwide. Early diagnosis and timely treatment can significantly reduce mortality rates and improve patient health outcomes. Traditional machine learning techniques provide moderate prediction performance; however, they often struggle to handle complex and high-dimensional medical datasets efficiently. This research introduced PredictHeart-X, a novel explainable deep learning framework for cardiovascular disease prediction. The proposed system integrates hybrid deep learning techniques with Explainable Artificial Intelligence (XAI) mechanisms to achieve high prediction accuracy, reliability, and transparency. The framework utilizes advanced deep learning architectures along with attention mechanisms to automatically learn hidden patterns from clinical healthcare data and accurately classify heart disease conditions. The incorporation of explainability methods such as SHAP and attention visualization enhances the interpretability of the prediction process by identifying the most influential clinical features contributing to disease prediction. This improves the trustworthiness and usability of the system for healthcare professionals

and supports effective clinical decision-making. Experimental analysis demonstrates that the proposed PredictHeart-X framework outperforms existing machine learning and deep learning models in terms of accuracy, precision, recall, F1-score, and reduced prediction errors. The hybrid architecture also improves feature learning capability and generalization performance while minimizing overfitting issues. Overall, the proposed system provides an intelligent, scalable, and interpretable solution for early cardiovascular disease prediction. The framework can assist doctors and healthcare institutions in identifying high-risk patients at an early stage, enabling timely medical intervention and improved patient care. Future enhancements may include integration with real-time IoT healthcare systems, cloud-based clinical platforms, and multimodal medical data such as ECG signals and medical imaging for further improving prediction efficiency and healthcare automation.

REFERENCE

- [1] M. Durairaj and V. Revathi, "Prediction of heart disease using back propagation MLP algorithm," *Int. J. Sci. Technol. Res.*, vol. 4, no. 8, pp. 235239, 2015.
- [2] Swamy, R. S., S. C. Kumar, and G. A. Latha. "An efficient skin cancer prognosis strategy using deep learning techniques." *Indian Journal of Computer Science and Engineering (IJCSE)* 12.1 (2021).
- [3] A. Gavhane, G. Kokkula, I. Pandya, and K. Devadkar, "Prediction of heart disease using machine learning," in *Proc. 2nd Int. Conf. Electron., Commun. Aerosp. Technol. (ICECA)*, Mar. 2018, pp. 12751278.
- [4] Sirisati RS, Kumar CS, Latha AG, Kumar BN, a Rao KS. An enhanced multi layer neural network to detect early cardiac arrests. In 2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA) 2021 Dec 2 (pp. 1514-1518). IEEE.
- [5] Mangesh Limbitote, Dnyaneshwari Mahajan, Kedar Damkondwar, Pushkar Patil, 2020, A Survey on Prediction Techniques of Heart Disease using Machine Learning, *INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH &*

TECHNOLOGY (IJERT) Volume 09, Issue 06 (June 2020),

[6] Sirisati RS, Kumar CS, Venuthurumilli P, Ranjith J, Rao KS. Cancer sight: Illuminating the hidden-advancing breast cancer detection with machine learning-based image processing techniques. In 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA) 2023 Nov 15 (pp. 1618-1625). IEEE.

[7] A. H. Alkeshuosh, M. Z. Moghadam, I. Al Mansoori, and M. Abdar, "Using PSO algorithm for producing best rules in diagnosis of heart disease," in Proc. Int. Conf. Comput. Appl. (ICCA), Sep. 2017, pp. 306–311.

[8] Bulla, Suneetha, et al. "A secure new HRF mechanism for mitigate EDoS attacks." International Journal of Ad Hoc and Ubiquitous Computing 40.1-3 (2022): 20-29.

[9] C. A. Devi, S. P. Rajamhoana, K. Umamaheswari, R. Kiruba, K. Karunya, and R. Deepika, "Analysis of neural networks based heart disease prediction system," in Proc. 11th Int. Conf. Hum. Syst. Interact. (HSI), Gdansk, Poland, Jul. 2018, pp. 233–239.

[10] SwamySirisati, R., Rao, M. S., & Thonukunuri, S. (2020, November). Analysis of Hybrid Fusion-Neural Filter Approach to detect Brain Tumor. In 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC) (pp. 460-464). IEEE.

[11] S.P. Bingulac, On the Compatibility of Adaptive Controllers, Proc. Fourth Ann. Allerton Conf. Circuits and Systems Theory, pp. 8-16, 1994. (Conference proceedings)

[12] Swamy, Sirisati Ranga, et al. "Multi-Features Disease Analysis Based Smart Diagnosis for COVID-19." Comput. Syst. Sci. Eng. 45.1 (2023): 869-886.

[13] AditiGavhane, GouthamiKokkula, Isha Pandya, Prof. Kailas Devadkar (PhD), Prediction of Heart Disease Using Machine Learning, Proceedings of the 2nd International conference on Electronics, Communication and Aerospace Technology (ICECA 2018). IEEE Conference Record # 42487; IEEE Xplore ISBN:978-1- 5386-0965-1

[14] Swamy, S. Ranga, et al. "Dimensionality reduction using machine learning and big data technologies." Int. J. Innov. Technol. Explor. Eng.(IJITEE) 9.2 (2019): 1740-1745.

[15] A.Lakshmanarao, Y.Swathi, P.Sri Sai Sundareswar, Machine Learning Techniques For Heart Disease Prediction, International Journal Of Scientific & Technology Research Volume 8, Issue 11, November 2019.

[16] Srinivasa Rao, P. S. V., Mekala Srinivasa Rao, and Ranga Swamy Sirisati. "A Hybrid Clinical Data Predication Approach Using Modified PSO." Smart Computing Techniques and Applications: Proceedings of the Fourth International Conference on Smart Computing and Informatics, Volume 2. Singapore: Springer Singapore, 2021.