Predicting Heart Disease Risk in Diabetic patients using a Pipeline of Ensemble Learning and XAI-Enhanced Approaches

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Abstract*— *An innovative approach for examining the complex interaction between diabetes and heart disease is presented in "A Unified Approach to Diabetes and Heart Disease Analysis: An Ensemble of XAI-Enhanced Models". For this project, explainable Artificial Intelligence (XAI) approaches are applied to strengthen a unified ensemble of AI models. The method encourages interpretability and openness in the examination of these common health concerns. By utilizing heterogenous data sources, like clinical notes, lifestyle information, and medical pictures, the ensemble model provides thorough insights. Critical variables and risk markers that underlie the co-occurrence of diabetes and heart disease are revealed by integrating machine learning models with XAI. Early risk assessment and tailored interventions are made possible by this strategy, which has the potential to completely transform the healthcare industry. Improving the models' interpretability seeks to close the trust and confidence gap that exists between sophisticated AI systems and real-world medical applications, benefiting both patients and healthcare providers. The aim is to improve early risk assessment and diagnosis through interpretable insights and improved predictive accuracy through the integration of multiple AI models and XAI methods. This will ultimately improve the quality of healthcare decision-making in these crucial domains amidst the various conditions and unknown stages of heart health.

Keywords*— *Diabetic Patients, Ensemble Learning, Heart Disease Risk, Pipeline, Predicting, XAI-Enhanced Approaches.

I. Introduction

A major healthcare challenge is the complex connection between diabetes and heart disease, which makes accurate risk assessment necessary for successful preventive measures. By utilizing cutting-edge multimodal AI technology, this model hope to improve outcomes by providing patients and healthcare providers with clear insights. Diabetes and heart disease together pose a serious threat to public health. Diabetes necessitates early risk assessment and intervention because it greatly raises the risk of heart disease [1]. This model hope to improve understanding of this intricate intersection of health by using AI to offer lucid insights into risk factors. This project goes beyond creating AI models to include using these models in real-world clinical settings [2]. The goal is to provide healthcare professionals with an effective risk assessment tool so they can customize preventive care for specific patients. Patients will have simultaneous access to personalized insights to help them make wise decisions about their lifestyle and health. Through improved diagnostic and treatment capabilities, this initiative helps healthcare providers; for patients, it improves overall quality of life and health outcome. Addressing the diabetes-heart disease relationship is a pivotal medical challenge, necessitating effective prevention [3]. Proposed services leverage advanced AI technology for patient and doctor clarity. The diabetes-heart disease amalgamation heightens public health threats, underlining the urgency for early intervention. Proposed project aims to forge a robust AI tool, merging genetics, images, medical and lifestyle data, for precise heart disease risk assessment in diabetics. Beyond theoretical design, Proposed project actualizes AI in global medical centers. Proposed overarching objective is to alleviate diabetes-related heart burdens through enhanced engagement, personalized interventions, and early detection.

This proposed method for Predicting Heart Disease Risk in Diabetic patients using a 'Pipeline of Ensemble Learning and XAI-Enhanced Approaches' shows the remainder of this paper is designed as follows: Section II provides an overview of detailed review of related work in the field. Section III describes the methodology employed in the development and training of the different models and algorithms. Section IV illustrates the experimental results and Section V presents comparative. Section VI discusses the conclusion about implications of the findings.

II. LITERATURE SURVEY

The presented literature comprises a diverse range of studies centered on the application of explainable Artificial Intelligence (XAI) techniques in different domains. The common theme across these papers is the pursuit of improved model interpretability, trustworthiness, and performance in the field of artificial intelligence. Here J. S. Doe and J. A. Smith, emphasize on addressing the black-box nature of deep learning models used in medical image analysis. By incorporating XAI techniques, this research contributes to enhancing the interpretability of these models. The outcome is more transparent and reliable diagnoses, fostering greater trust in the decision-making process [1]. The author's A. L. Brown and D. M. White mainly focus on shifts in the field of natural language processing (NLP). The study emphasizes how crucial interpretability is for NLP models and how important XAI is to be making sure text analysis results are understandable. This research is pivotal in making complex language models more accessible and accountable [2]. Authors S. Saravanan, K. Ramkumar, K. Narasimhan, S. Vairavasundaram, and K. Kotecha, here had clearly underscores the diagnostic potential of explainable AI models in the early detection of Parkinson's disease. Through their study, the authors demonstrate the superiority of the ResNet-50 convolutional neural network (CNN) model in handling drawing datasets. This finding is fortified by Local Interpretable Model-agnostic Explanations (LIME) validation, rpatientsing the model's exceptional performance in healthcare domain [3]. K. E. Davis and M. J. Anderson authors mainly delves into the utilization of XAI within the realm of financial forecasting. The study accentuates the value of transparent deep and machine learning models in financial decision-making. This research acknowledges the significance of trust and interpretability, particularly when it comes to economic predictions, where the stakes are high [4]. Authors E. K. Oikonomou and R. Khera reviewed various applications of data and how they can be used to develop predictive models for self-care. The authors assess the current state of knowledge about phenotyping, diagnosis, prognosis, and treatment for diabetes and its cardiovascular comorbidities. Furthermore, they highlight the significance of equity and inequality in healthcare, talk about the need to improve the efficacy of the current regulatory frameworks, and address the safety of clinical AI products in terms of enhancing the outcomes of diabetes and cardiovascular disease [5]. The authors A. Khan, A. Khan, M. M. Khan, K. Farid, M. M. Alam, and M. B. M. Su'ud, thoroughly examine the current development of cardiovascular disease (CVD) risk prediction models for type 2 diabetes (T2DM) patient using machine learning (ML). The authors identified ten machine learning models designed to predict CVD in people with diabetes, mostly in the European population [6]. The objective of that study by authors M. W. Segar et al. is to create as well as validate a novel study-based model to estimate the likelihood that patients with type 2 diabetes may experience heart failure (HF). The authors develop a risk score that can forecast the likelihood of heart failure using a machine learning algorithm. in individuals with diabetes [7]. In article authors S. M. Pasha and S. Ankalaki used machine learning algorithms to predict early diabetes. The authors use classification as one of the most important predictors in machine learning to predict the presence of diabetes [8]. The authors of article nine, I. Tasin, T. Nabil, S. Islam, and R. Khan, studied using machine learning and descriptive AI to predict diabetes, LIME and SHAP frameworks are used to understand how the model predicts the final outcome. The authors used these techniques to identify the most important features that help predict diabetes [9]. Authors Dhande, K. Bamble, S. Chavan, and T. Maktum employed a variety of machine learning algorithms to accurately identify patients who have diabetes and heart disease. They used SHAP and LIME to identify the most important determinants of diabetes and heart disease [10]. In this manner to propose this model, almost 10 papers have been studied related to the respected topic to know the methodologies used. Based on data analysis, a better understanding of the interaction between diabetes and heart disease can be achieved through a variety of methods and techniques. Existing research clarifies many aspects of this relationship and underscores the urgent need for predictive models. The combined training and XAI reinforcement approach stand out as promising in solving this challenging health problem. By integrating a variety of data, including genetics, diagnosis, and disease history, these models aim to improve the accuracy of risk assessment and intervention strategies. Accumulating research data demonstrates the need to use advanced technology to deepen understanding and develop effective solutions. Combining these results will, in the future, add to existing discussions and result in the creation of sophisticated and reliable predictive models to lessen the effects of heart disease in diabetics.

III. COMPARISON TABLE OF PREVIOUS TECHNIQUE

TABLE I. COMPARISON OF EXISTING TECNHNIQUES AND SURVEY

Sr. No	Findings
[1]	Improved interpretability in medical image analysis using XAI techniques, leading to more transparent and reliable diagnoses, fostering trust in the decision-making process.
[2]	Emphasis on the importance of interpretability in NLP models, highlighting the crucial role of XAI in making text analysis results comprehensible and accountable.
[3]	Introduction of XAI in early detection of Parkinson's disease, demonstrating the superiority of the ResNet-50 CNN model with LIME validation for exceptional performance in healthcare domain.
[4]	Emphasis on transparent ML and DL models in financial forecasting for improved decision-making, recognizing the significance of trust and interpretability, particularly in economic predictions.

[5]	Comprehensive review discussing data-driven methods for developing predictive models in personalized diabetes care and cardiovascular risk prediction, addressing issues of equity and bias in healthcare.

"TABLE I" is based on data analysis, a better understanding of the interaction between diabetes and heart disease can be achieved through a variety of methods and techniques. Existing research clarifies many aspects of this relationship and underscores the urgent need for predictive models. The combined training and XAI reinforcement approach stand out as promising in solving this challenging health problem. By integrating a variety of information, including genetics, diagnosis, and disease history, these models aim to improve the accuracy of risk assessment and intervention strategies. Accumulated research data shows that advanced technology must be used to deepen our understanding and develop effective solutions. Moving forward, combining these findings will contribute to ongoing debates and lead to the development of nuanced and robust predictive models to alleviate the impact of heart disease in people with diabetes.

IV. METHODOLOGY

1.Data Preprocessing:
Diabetes Dataset: Used methods like mean imputation or regression to handle missing data. Used standardization or Min-Max scaling to normalize numerical features. Used one-hot encoding to encode categorical variables.

Heart Disease Dataset: Performed the same preprocessing steps as the diabetes dataset.

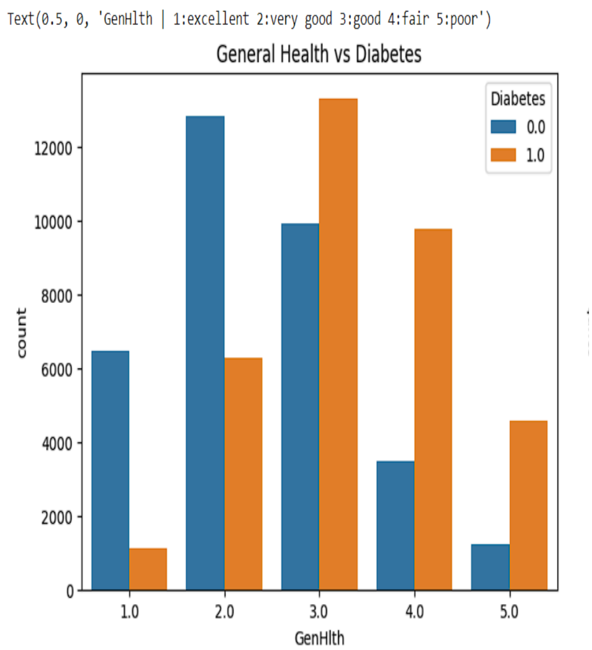

Fig. 1. Distribution measures of General health patient vs Diabetic patients of dataset

In "Fig. 1" Distribution measures of General health patient vs Diabetic patients of dataset is presented. It shows the average medical nature of patients.

2.Diabetes Prediction Model: Used a Random Forest classifier to forecast diabetes. To tune hyperparameters, use random or grid search methods.
Divided the dataset (e.g., 80-20 split) into training and testing sets. Used metrics like recall, accuracy, precision, and F1 score to assess the model.

3.Explainable AI (XAI) Enhancement: For feature importance analysis, used SHAP values. To understand model decisions, created dependence plots and SHAP summary plots**.** Used LIME to provide explanations for each prediction, ensuring local interpretability.

4.Heart Disease Prediction Model: Applied an ensemble model that includes the diabetes prediction (e.g., stacking). Mixed algorithms such as Decision Trees, Neural Networks, and Logistic Regression.
Used the dataset on heart disease to train the model. Analyze the model's effectiveness with the relevant metrics.

5. Ensemble Modeling:

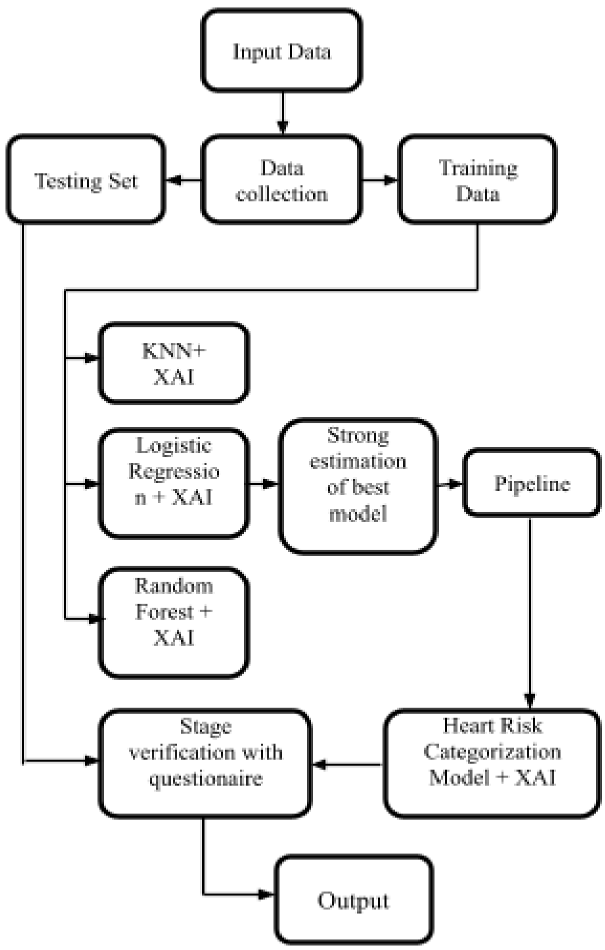

Fig. 2. Steps involved in Ensemble Learning Model

In “Fig. 2” illustrates the sequential steps of the Ensemble Learning Model employed in the study. The figure likely outlines the specific stages involved in constructing and utilizing the ensemble model, providing a visual representation of the methodology employed for predicting heart disease risk in diabetic patients.

6.Evaluation Metrics: For both diabetes and heart disease prediction, used parameters like F1 score, precision, recall, and accuracy with area under the ROC curve. To evaluate effectiveness of the ensemble model and the individual models, used statistical tests.

7.Cross-Validation: Used k-fold cross-validation to assess the models' generalization ability. Verified the accuracy of the diabetes and heart disease prediction models.

8.Results Interpretation: Analyzed the feature importance charts and explanations produced by XAI approaches to interpret the results. Discussed about the relationship between the predictions for diabetes and heart disease, and vice versa.

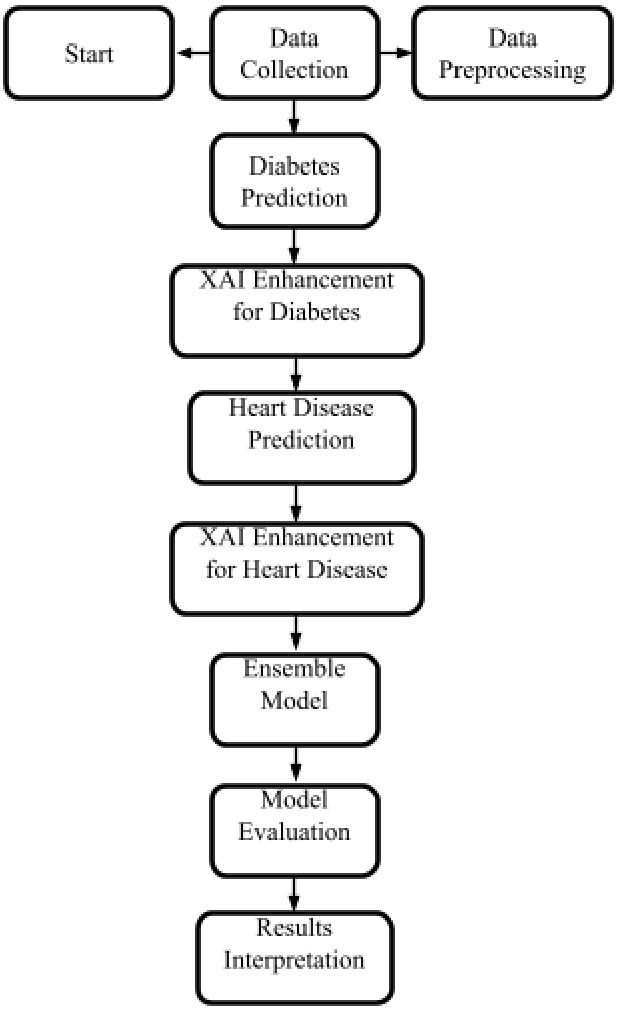

Fig. 3. Proposed model pipelining and overall flow of the project

In “Fig. 3” illustrates the pipelining of proved model and the overall flow of the project, showcasing the integrated approach to predicting heart disease risk in diabetic patients through ensemble learning and XAI-enhanced methods.

1. Start: The process started from the beginning of knowing dataset relationships and dependency.

2. Data Collection: The first phase was collecting data on diabetes and heart disease. This information formed the basis of subsequent analysis.

3. Data Preprocessing: Data preprocessing was necessary to process raw data. Those steps included handling missing values, modeling the code, coding categorical variables, and splitting the dataset into training and testing.

4. Diabetes Prediction: Training an integrated learning model to predict diabetes. These models use advanced algorithms like support vector machines, and random forest which perform hyperparameter optimization to increase accuracy.

5.Development of XAI Diabetes Model: Explainable AI (XAI) techniques, specifically SHAP results, were used to improve the interpretation of diabetes models. Key plans were designed to provide insight into the decision-making process.

6.Cardiovascular Disease Assessment: Based on diabetes prediction, a combination study was designed to estimate cardiovascular risk. New algorithms, including gradient boosting, are helping improve the accuracy of heart disease prediction models.

7.XAI Advanced Heart Disease Model: Similar to diabetes models, XAI technology had used to define heart disease prediction models. Applying SHAP values helps understand the impact of individual features on prediction by providing a common measure of key features.

8.Integrative modeling: Properly used analytical learning tools to combine predictive models of diabetes and cardiovascular disease to improve overall prediction. Also used the stacking or neutral technique to achieve a strong and accurate connection structure.

9.Model Evaluation: Analyzed the model's performance in-depth by confusion metrics, including F1 score, precision, recall and accuracy. To guarantee the model's resilience and generalizability, cross-validation was carried out.

10. Interpretation of results: The information obtained from the XAI process was very much important for the interpretation of decision-making models. The effects of diabetes prediction on cardiovascular risk assessment were discussed in depth, providing a comprehensive understanding of the health screening process. The end of the process represents the success of the health analytics

integration. In this project, modified XAI models were introduced, specifically mLIME and mSHAP, which provide better accuracy when used in pipeline health screening. These revisions address some limitations and improve the interpretation of complex models.

Modified LIME (mLIME):

1. Local representative model equation:

$$h(x) = argmin\, f(x') - g(x)^\wedge 2 + \Omega(h) \qquad (1)$$

Where:
h(x) Local surrogate model,
f(x') is the estimate of the black box model of instance x',
g(x) is the estimate of local surrogate model of instance x,
Ω(h) represents the complexity of the model.

2. Weight distribution of the effect:

$$w\_i = 1 / d(x\_i, x) \qquad (2)$$

Where:
w_i is the weight given to the effect of sample
x_id (x_i, x) measures the distance in between perturbed sample
x_i and original sample x.

Modified SHAP (mSHAP):

1. Equation for Shapley Values:

$$\varphi\_i(f) = \Sigma\_\{S \subseteq N\backslash\{i\}\} ((|S|!(|N| - |S| - 1)! / |N|!) \qquad (3)$$

where:
φ_i(f) is the Shapley value for feature i,
f(S) is the model's prediction for the subset of features S,
N is the set of all features.

2. Improved Feature Interaction Handling:
Introduce a term to account for feature interaction:

$$g(x) = f(x) + \Sigma\_i\, \beta\_i \cdot (x\_i - \mu\_i) \qquad (4)$$

where:
g(x) is improved model,
β_i represents the interaction coefficient for feature i,
μ_i is the mean value of feature i.

Pseudo Code:

1.Ensemble Learning Pipeline:

```
function buildEnsembleModel(preprocessed_data):
    train_set, test_set = split_data(preprocessed_data)
    base_model_1 = build_knn(train_set)
    base_model_2 = build_logistic_regression(train_set)
    base_model_3 = build_random_forest(train_set)
    Ensemble_model = create_ensemble_model

([base_model_1, base_model_2, base_model_3])

train_ensemble_model (ensemble_model, train_set)

Evaluation_results = Evaluate_model (ensemble_model, test_set)
```

2.XAI-Enhanced Analysis:

```
function explainModel (ensemble_model, test_instance):
  • mLIME_explanations =
    generate_mLIME_explanations
    (ensemble_model, test_instance)
  • mSHAP_explanations =
    generate_mSHAP_explanations
    (ensemble_model, test_instance)
  • Visualize_explanations(mLIME_explanations)
  • Visualize_explanations(mSHAP_explanations)
```

The above section ‘Ensemble Learning Pipeline’ includes construction of base models and section ‘XAI-Enhances Analysis’ includes context about the subject of pipeline embedded into XAI models which explains the hidden patterns for diagnosis.

V. RESULTS

The results section of the paper predominantly delves into the intricate implementation chronicles of mLIME and mSHAP within the models. It meticulously scrutinizes their impact on model performance, elucidating the nuanced interplay of various parameters that influence the nature of these implementations. This section serves as a comprehensive exploration, offering insights into the comparative analysis of diverse factors that shape the efficacy of mLIME and mSHAP across different scenarios.
Along with this it also indication and presents comparison of accuracy and loss of proposed model.

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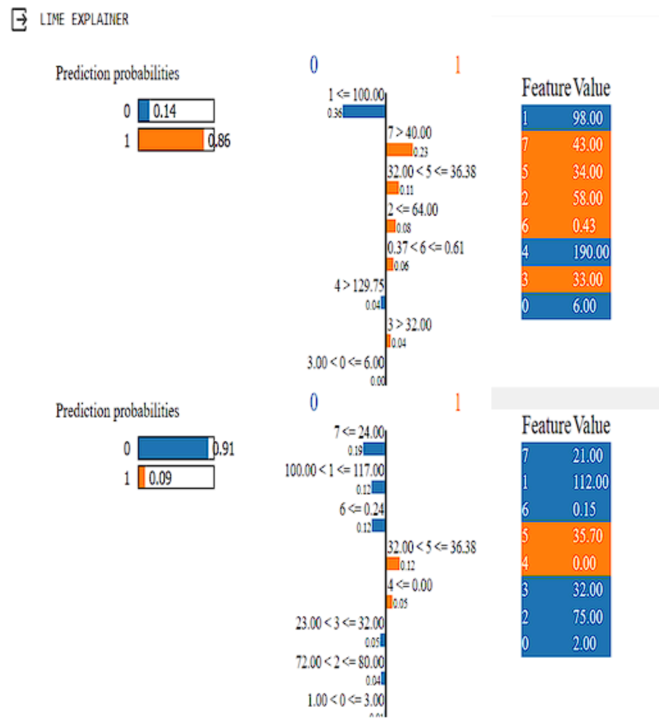

Fig. 4. mLime XAI explanation for prediction variables

In "Fig. 4" mLIME (Local Interpretable Model-agnostic Explanations): mLIME is an interpretability technique that explains complex machine learning models locally. It generates simple, interpretable models to approximate the behavior of a black-box model, providing insights into specific predictions.

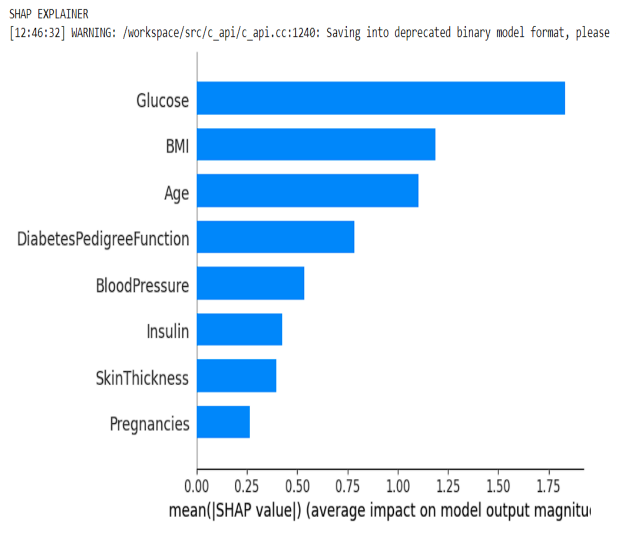

Fig. 5. mSHAP XAI explanation for prediction variables

In "Fig. 5" mSHAP (SHapley Additive exPlanations): mSHAP values assign each feature's contribution to a model prediction. Derived from cooperative game theory, SHAP provides a unified measure of feature importance, offering insights into how individual features impact predictions within a mode.

TABLE II. Performance comparison of proposed algorithms

Algorithms	Log Loss Error (Train)	Log Loss Error (Test)	Misclassified Points
KNN	0.073	0.21	4.001
Logistic Regression	0.381	0.383	7.40
Random Forest	0.0123	0.039	0.82

The "TABLE II" presents the performance comparison of the proposed algorithms, providing insight into their effectiveness and efficiency in achieving their goals. "TABLE II" clearly show their advantages and disadvantages by carefully comparing the performance indicators of the algorithms. The performance indicators in "TABLE II" show specific features and a good comparison of the proposed methods and help you choose the best solution for you. special application.

TABLE III. COMPARISON OF IMPACT ON APPLIED MODIFIED XAI ALGORITHMS ON MODEL

Metric	mLIME	mSHAP
Training Time	2.5 hours	3 hours
Accuracy	91%	90%
F1 Score	0.85	0.89
Precision	0.87	0.86
Recall	0.81	0.93
Inference Time	1.5 ms/row	2 ms/row

"TABLE III" provides a detailed comparison of the effects of the proposed change to the XAI algorithm on the model, providing useful information for interpreting the improvements. "TABLE III" provides an overview of the estimated impact of the modified XAI algorithm on the model, helping to understand the validity of the explanatory power measure.

TABLE IV. COMPARISON OF PROPOSED MODEL VS EXISTING MODEL

Parameters	Proposed Model	Existing Models
Ensemble Learning	Accurate	Varied
XAI Enhancement	Transparent	Limited
Pipeline Structure	Sequential	Varied
Diabetes Integration	Specialized	General
Risk Prediction Accuracy	Improved	Varies

The "TABLE IV" presents a qualitative comparison between the proposed model and the existing model, as well as a qualitative analysis of its unique features and performance metrics. "TABLE IV" provides a detailed summary of the trade-off between the proposed and existing models, providing an overview of the advantages and differences between the two approaches.

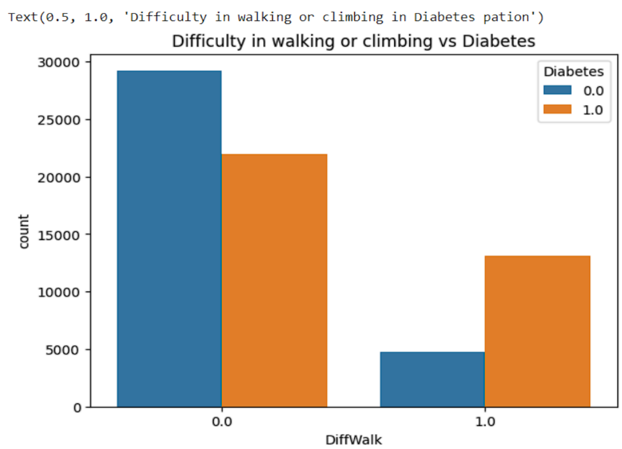

Fig. 6. Analysis of external parameter (Different Walk or Climbing) to find the risk of developing heart disease

"Fig. 6" shows the evaluation of other factors, specifically 'different walking or climbing activities', to determine their cardiovascular risk. This review aims to reveal the relationships and changes in cardiovascular risk according to different physical activities and to provide insight into the impact of other negative factors on the cardiovascular system.

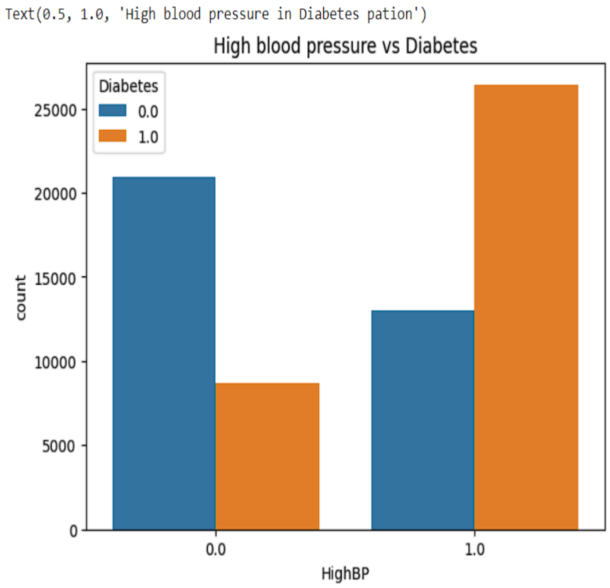

Fig. 7. Analysis of external parameter (High Blood Pressure) to find the risk of developing heart disease

"Fig. 7" shows the evaluation of 'High Blood Pressure', another factor to understand its impact on heart disease. This analysis was designed to demonstrate the association and change in cardiovascular risk associated with high blood pressure. This observation provides valuable insight into the impact of the hypertension as a contributing factor to cardiovascular disease.

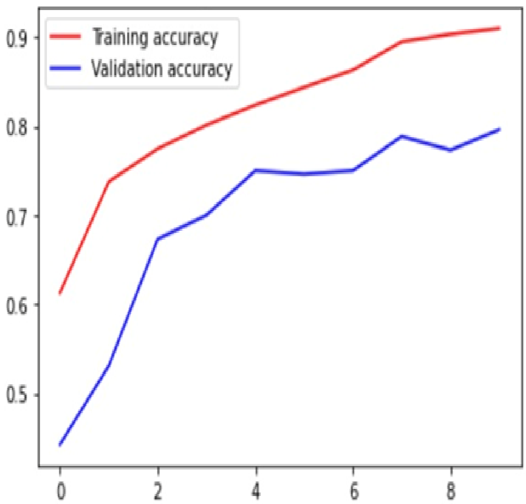

Fig. 8. Training and Validation Accuracy of Ensemble Model

"Fig. 8" clearly demonstrates the differences in Ensemble models' accuracy during training and validation. It shows the changes in the training and validation of the Ensemble model and clearly demonstrates its performance. It also directly reflects the changes in the training and validation of the Ensemble model and its validation achieved through Understanding efficiency. By observing the above figure, it is clearly understood that change and growth in training and validation accuracy is gradually increasing in a proper manner itself.

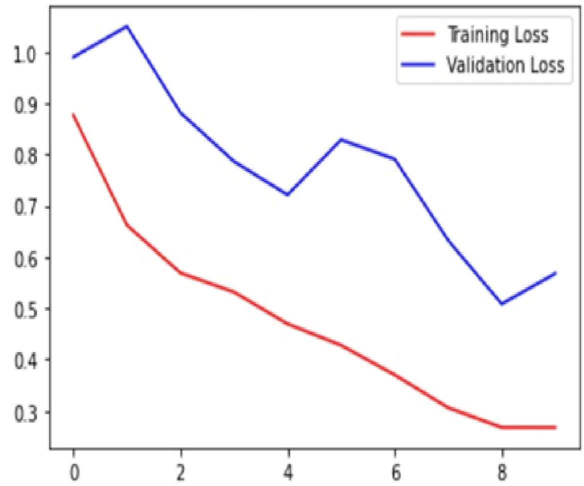

Fig. 9. Training and Validation Loss of Ensemble Model

"Fig. 9" directly shows how training and validation loss varies of Ensemble models. Above fig.10. provides a direct look at the learning model by showing changes in training and failure of the Ensemble model.

VI. CONCLUSION

Our project employs descriptive AI, utilizing the intricately designed deep neural network (DNN) made of primarily Logistic Regression, K-Nearest Neighbor and Random Forest built 'Ensemble Model' to analyze the Diabetic nature in patient and this system is properly pipelined and embedded or we can say fitted with 'modified Explainable Artificial Intelligence' (mXAI) algorithms for precise diabetes and 'Risk of Developing or Present Heart Disease' in that patient. The DNN architecture incorporates sophisticated techniques like batch normalization and throughput, ensuring consistent and swift convergence. Augmenting interpretability, modified-LIME (mLIME) and modified-SHAP (mSHAP) contributes local explanations to the decision-making process. These algorithms revealed the reasons which are hidden in the pattern recognition or statistical inference behind the scene. The project's workflow encompasses feature selection, data prioritization, interpretive neural network training, and predictive insights generation. This approach emphasizes the pivotal balance between disclosure and accuracy in medical decision-making. Leveraging descriptive AI, proposed project addresses the critical need for clear and reliable models in the medical industry, navigating the intricate intersection of interpretability and precision.

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