Early Diabetes Prediction using Machine learning techniques with XAI

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***Abstract*—Diabetes is a disease that slowly starts to deteriorate the health of an individual and is seen to be rising among the majority of people with time. It can be caused due to hereditary or dietary reasons and lead to an impact on different other parts of the body and create an unhealthy and disastrous lifestyle. In order to detect this incurable and fatal disease this study aims to predict the occurrence of diabetes in a person using machine learning algorithms. The study employs nine supervised and unsupervised learning techniques to analyze a large dataset of medical records. The XAI (Explainable Artificial Intelligence) approaches SHAP and LIME are used to interpret the model's predictions and provide explanations for the results.**

***Index Terms*—Diabetes, Machine Learning, Logistic Regression, Random Forest Classifier, Decision Tree, K-Nearest Neighbor(KNN), XGBoost, Multi layer Perceptron, AdaBoost, LightGBM**

I. Introduction

Millions of individuals throughout the world suffer from the chronic disease diabetes, which is a leading cause of mortality, morbidity, and disability. Diabetes is a dreadful condition brought on by either insufficient insulin production by the pancreas or inefficient insulin utilization by the body [1]. There can be two types of diabetes: type-1 diabetes is caused by insulin deficiency and occurs mostly in children between 5-7 years of age. [2] Type-2 diabetes is present in more than 90% people with this disease [3] and is caused by ineffective use of insulin. This type was mainly seen in people above 25, but recently Type-2 has also been detected among younger people. Aside from the symptoms of Diabetes, it can cause damage to other organs of the human body such as the heart, nerves, eyes, kidneys, liver, and even the nervous system. The immunity of an individual may also get lower due to having Diabetes. Patients are more prone to have cardiovascular diseases such as heart attacks and strokes [8]. Moreover, a significant contributor to blindness, diabetic retinopathy results from cumulative long-term harm to the retina's tiny blood vessels [9]. It also puts an effect on the pregnant women and the baby [23], causes kidney failure, and other health issues.

Diabetes may be prevalent for four to twelve years before diagnosis, according to research [10]. If diabetes is not adequately controlled, it can have both short and long-term consequences and lead to complications. To manage the disease and avoid any health damage, early diagnosis, and prompt management are essential. According to the International Diabetes Federation (IDF), around 463 million people had diabetes in 2019, 537 million people had diabetes in the world in 2023, and 90 million people in the SEA Region. This number is expected to rise to 155.1 million by 2045 [15]. Thus calculating the risk factors and their severe effects on the quality of life this paper tries to evaluate different machine learning models and their performances to detect early diabetes.

Machine learning techniques have shown great potential in predicting the onset of diabetes using various clinical and demographic features. ML models such as Support Vector Machine(SVM), Logistic Regression, Random Forest Classifier, Decision Tree, K-Nearest Neighbor(KNN), XGBoost, Multilayer Perceptron, AdaBoost, LightGBM have been evaluated to predict early diabetes present in the patient or not based on the data received. The UCI Machine Learning Repository [17] has been used for training the models and evaluation purposes. For better interoperability of the ML models, we use a merging discipline explainable AI (XAI) that seeks to make machine learning models transparent and understandable so that both clinicians and patients can use them with confidence. We will use XAI techniques such as Shapley Additive explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) to explain the factors that contribute to the prediction.

II. Related Works

There are many types of research that have been done on the early detection of diabetes using machine-learning techniques. In this section, we are highlighting some of them which have made prominent contributions in the area of early diabetes disease detection.

In the year 2021, Abdulhadi and Al-Mousa [4] proposed a research work that predicts the possible presence of diabetes -specifically in females- at an early stage. The work focused on predicting type-2 diabetes and the authors used Pima Indian dataset [5] in their work. They used various ML algorithms such as Logistic Regression, LDA, SVC, Linear SVC, Random Forest, and voting classifier where the Random forest showed the best accuracy of 82%. Another paper in the same year by Hassan et al. [6] also focused on detecting early diabetes using machine learning classifiers like Logistic Regression, Random Forest, and XgBoost. They used a dataset collected from Khulna Diabetes Center, Khulna, Bangladesh which had 289 samples of type -2 diabetes. Among the classifiers, Logistic Regression performed well and achieved 88% accuracy. In another work [7] authors used A publicly available dataset of 520 people with 16 features with eight machine learning models to detect early-stage diabetes. The Random Forest classifier achieved the highest accuracy of 98.31%. A comparative analysis regarding the same topic is discussed by Refat et al. [11] where Machine learning(XGBoost, Random Forest, Decision Tree, KNN, etc) and Deep learning techniques(ANN, MLP, LSTM) have been used for comparison. They used the UCI dataset with 17 attributes and the XGBoost classifier achieved an accuracy of nearly 100% and the lowest accuracy was recorded using the KNN classifier. Apratim Sadhu, Abhimanyu Jadli [12] also used the UCI dataset to predict early-stage diabetes using seven machine learning classifiers. They used accuracy, F1 score, and ROC to measure the performance of their models. Here also the Random Forest classifier outperformed others by nearly 98% accuracy. Adding to the list of research done on detecting diabetes in the year 2021, the authors proposed a method of incorporating data mining techniques to predict the disease [13]. They collected their data from the sector of statistics of the Public Health Institute and used that in the WEKA [14] environment. Simple Logistic, MLP, Logistic, Naive Bayes, Bayes Net, SMO, and C4.5 are used as prediction techniques among which the c4.5 decision tree showed better performance with 79% accuracy. Salliah Shafi and Prof. Gufran Ahmad Ansari also did research on predicting early-stage diabetes disease using machine learning techniques such as SVM, Naive Bayes, and decision trees where they proposed a framework that estimates the diabetes disease with maximum precision. They have also used the Pima Indian Dataset from the UCI library. The primary aim of this research was to use the WEKA tools to predict the disease. As performance measurement techniques, they used Certainty, Precision, Recall, F-measure, and ROC. The Naive Bayes classifier got 74.28% accuracy whereas SVM got only 63.10% accuracy. Another paper [] uses ML models and analyzes why ML models do not show stable results in this area. They have also taken the computational time into account to decide the best-performing model for detecting the disease. The authors collected datasets from two sources: an automatic electronic recording device and paper records. Eight features were recorded in the dataset including Pregnancy, Glucose, Blood pressure, Insulin, BMI, etc. Random Forest classifier here also outperforms others with 80% accuracy. In the year 2020, MINH LE et al. [19] A novel wrapper–based feature selection for early diabetes prediction. In their proposed model authors have used the Multi-Layer Perceptron and optimized using the Grey Wolf Optimization (GWO) and an Adaptive Particle Swam Optimization (APSO). They successfully reduced the number of required attributes of MLP and achieved better performances than the state-of-art models when compared. To preprocess the dataset which is collected from [20] they used the IQR method. In terms of performance., 96% accuracy for GWO- MLP and 97% for APGWO - MLP was achieved. In 2022, Dutta et al. proposed a method of identifying diabetes at an early stage using an ensemble of machine learning models. They introduced a new database on diabetes from Bangladesh. They used a weighted ensemble of NB, RF, DT, XGB, and LGM. They also performed a feature selection and K-fold validation on their model. ANOVA test showed that by ensembling DT + RF + XGB + LGB, the proposed model achieves an accuracy of 73.5%.

From the above discussion, we can see that over time and specifically in the recent time frame many studies incorporating and visualizing the performance of Machine learning models in the area of diabetes detection at an early stage have been made. Most of the works have achieved previously expected satisfactory results using models like Random Forest or decision trees. However, the development of diabetes diagnosis currently is still in the impoverished phase due to the dearth of effective and robust models with explanations, despite the fact that various ML-based solutions have previously been published in numerous research articles. We tend to analyze the performance of these ML models with the help of XAI and discuss what can be done the improvement of performances.

III. Dataset

For our research, we have used the publicly available Early stage diabetes risk prediction dataset of the UC Irvine(UCI) Machine Learning Repository [22]. This dataset has 520 instances with 16 attributes. This has been collected using direct questionnaires from the patients of Sylhet Diabetes Hospital in Sylhet, Bangladesh, and approved by a doctor. 15 attributes or features are categorical and 1 among them is labeled as continuous. Some of them are in medical terms such as Polydipsia(extreme thirst), Polyphagia(excessive hunger), Thrush(a form of yeast infection), Blurred vision(loss of clear vision), Paresis(weakness of voluntary movement), Muscle stiffness(Tight muscles), and Alopecia areata(hair loss in the

TABLE I: Dataset Attributes with Example

Attribute Name	Values	Example of The Data
Age	20-65	58
Sex	Male Female	Male
Polyuria	Yes No	No
Polydipsia	Yes No	No
Sudden Weight Loss	Yes No	No
Weakness	Yes No	Yes
Polyphagia	Yes No	No
Genital thrush	Yes No	No
Visual blurring	Yes No	Yes
Itching	Yes No	No
Irritability	Yes No	No
Delayed Healing	Yes No	No
Partial Paresis	Yes No	Yes
Muscle Stiffness	Yes No	No
Alopecia	Yes No	Yes
Obesity	Yes No	No
Class	Positive Negative	Positive

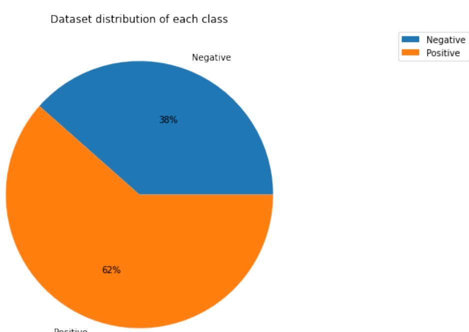


Fig. 1: Dataset Distribution

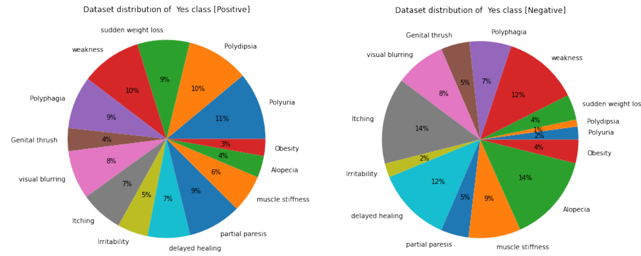
body) The attribute information of the dataset is shown in the table I.

A. Dataset Distribution

While working with classification-related tasks it is very important to analyze the dataset and visualize the class-wise feature distribution for a better understanding of the dataset.

In our dataset, there are 62% of positive class meaning diabetic class and 38% of healthy class as shown in the figure 1

From figure 3, we can see the feature-wise distribution for each class and get an overall idea about the impacting features of the classes like from figure 3(a) is seen that in the positive class, the majority of persons are female (around 173) indicating a high risk of diabetes among female individuals.



(a) Positive Class (b) Negative Class

Fig. 2: Impact of Features in Class Distribution

Another interesting aspect is the vast presence of Polydipsia among diabetic patients which is shown in 3(c) around 225 persons who have polydipsia are diabetic. Again from figure 3(p) it can be seen that there are 259 people who are not obese but diabetic. It can indicate that although obesity may not be present in a patient but a person may still be diabetic. The whole feature-wise distribution for a specific class can be found in figure 2.

IV. Methodology

A. Pre-processing the data

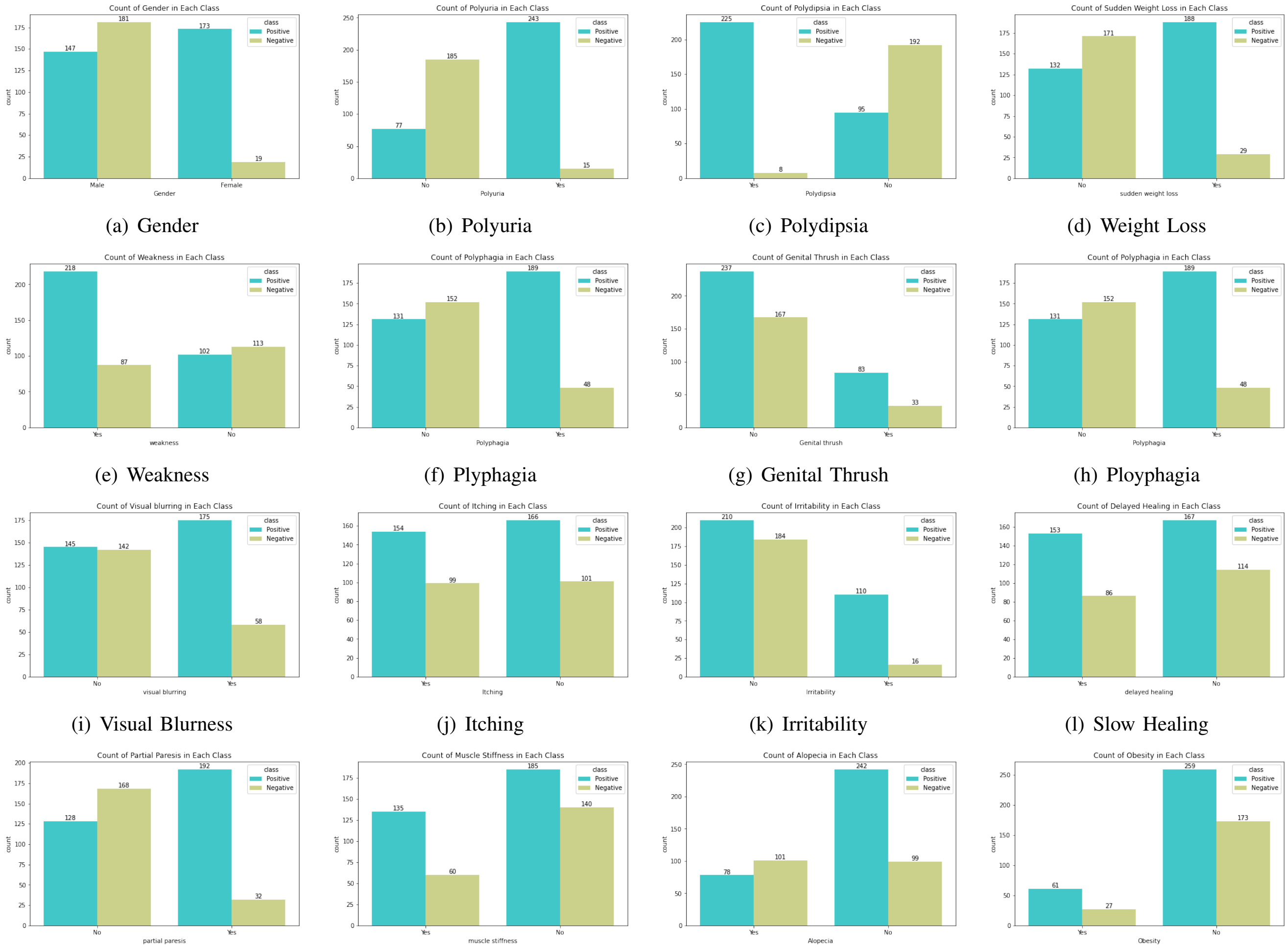
Since our dataset contained attributes/features that had categorical values such as male, female, yes, no, positive, and negative we have converted these values to numerical data for improving interpretability and simplifying the data representation. We have normalized our dataset to bring all the values to the common range which can improve model performance and ensure convergence.

B. Correlation of The Features

After analyzing the dataset we have also tried to understand the correlation between the features of the dataset. Correlation between two variables helps to understand how much the variables are close to one another and can have an effect on the other positively or negatively. We have used Pearson's [25] correlation shown in figure 4. Based on the correlation, the top 10 features with the highest values are taken to understand the impact of these features on our result. We have trained the models with these top 10 selected features ad well as all 16 features to produce a better comparison.

C. Machine Learning Models

In order to train the model and build a comparison between machine learning models we have used different classifiers. The overall process is shown in figure 5. These are discussed in brief as follows:



(a) Gender (b) Polyuria (c) Polydipsia (d) Weight Loss

(e) Weakness (f) Plyphagia (g) Genital Thrush (h) Ployphagia

(i) Visual Blurness (j) Itching (k) Irritability (l) Slow Healing

(m) Partial Paresis (n) Muscle Stiffness (o) Alopecia (p) Obesity

Fig. 3: Attribute wise Class Distribution

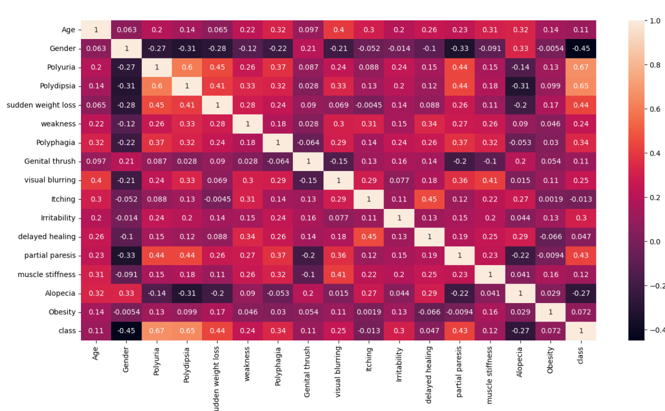


Fig. 4: Correlation between the features of the dataset

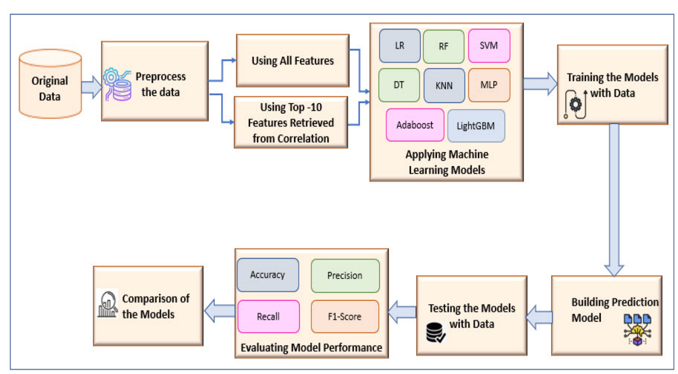


Fig. 5: System Architecture of the Entire Process

1) Logistic Regression: It [26] is a binary classifier that falls under the type of supervised learning technique, using a predetermined set of independent factors to predict the categorical dependent variable. It outputs a binary score based on which we determine whether the patient is diabetic or not.

2) Random Forest Classifier(RF): Random Forest(RF) [27] used for classification and regression task was another algorithm that we have used. RF is quite strong while identifying overfitting and can be quite efficient. Additionally, it can manage missing values in the data and be applied to feature selection.

3) Support Vector Machine(SVM): Support vector machine(SVM) [28] used for classification tasks tries to locate the hyperplane which maximizes the margin between the various classes of the data provided. We have used this to understand the results and how our model performed on our data.

4) Decision Tree(DT): Decision tree [29] is a machine learning technique that builds hierarchical structure by partitioning the data into smaller subsets based on the features. By learning straightforward decision rules inferred from the data attributes, the objective is to build a tree that predicts the target variable. This technique can be beneficial in classification and regression tasks and also handle categorical or numerical data.

5) K-Nearest Neighbor(KNN): KNN [30] is a nonparametric algorithm that tries to make predictions based on the similarity of the data points on which it has been trained and the distance metric provided. When using regression or classification, KNN determines the majority class (classification) or mean value (regression) based on the distances between the query data point and the training set. Finding the value of K can become complex and act as a disadvantage.

6) Multi-layer Perceptron(MLP): MLP [31] is a well-known neural network architecture made up of numerous layers of interconnected nodes that process the input data and discover intricate patterns through back-propagation. This process creates a nonlinear function model that makes it possible to predict output data from the input data. Images, text, and time series data can all be used with MLP. It can also handle the non-linear correlations between the input and output variables based on the data types.

7) AdaBoost: For classification tasks, a common ensemble learning technique called AdaBoost (Adaptive Boosting) [32] is utilized. It functions by rating the significance of each sample according to its classification performance and iteratively training weak classifiers on the misclassified examples. The combined weighted votes of the weak classifiers yield the final prediction. There are other boosting algorithms but AdaBoost can manage noisy data and increase the accuracy of the underlying classifiers.

8) LightGBM: Light GBM (Light Gradient Boosting Machine) [25] is an effective gradient boosting system that can handle big datasets with high-dimensional features. It is also made to be effective, scalable, and versatile. To increase this algorithm's precision, Light GBM applies a gradient-based optimization technique with a tree-based model. It also uses a histogram approach to minimize the computation cost while splitting.

D. Evaluation Matrices

A variety of performance metrics were used in this investigation to explain why ML models could perform well with one evaluation metric's measurement while performing not so great with another metric's assessment. Different evaluation criteria must be used to make sure an ML model is functioning properly and optimally. In this study, we mainly used Accuracy, Precision, Recall, and F1-Score as performance evaluation metrics.

1) Accuracy: Accuracy is defined as the total number of accurate predictions divided by the total number of data samples present in the dataset as shown in the equation (1)-

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

2) Precision: The Precision is defined as the total number of accurate positive predictions divided by the total number of positive predictions as shown in the equation (2)-

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

3) Recall: The recall is defined as the total number of accurate positive predictions divided by the total number of actual positive predictions as shown in the equation (3)-

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

4) F1-Score: F1-Score is the harmonic mean of precision and recall as shown in the equation (4)-

$$F1{-}Score = \frac{2*Precision*Recall}{Precision+Recall} = \frac{2*TP}{2*TP+FP+FN} \tag{4}$$

Here,
TP = True Positive , TN = True Negative
FP = False Positive, FN = False Negative

V. Experimental Results and Discussion

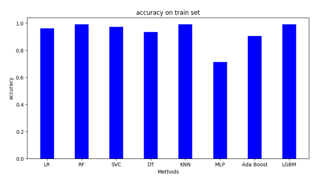
The diabetes risk prediction dataset is used to test each of the aforementioned machine learning models, and the results are stored in terms of accuracy, precision, recall, and f1-score.

To detect diabetes in an early stage we used our dataset in two approaches. We wanted to experiment and compare to find out the most effective model for predicting the outcome. First, we used all of the features present in the dataset in our models and predicted the outcome. In a second approach, we used only the top 10 features and used them in our aforementioned models to predict the outcome. The detailed comparison of evaluation metrics results can be found in the table II.

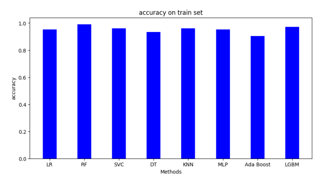
From table II, we can see the performance comparison of both of our approaches. It is evident that, in both of the approaches Random Forest classifier outperformed all other classifiers. It achieved equal accuracy, precision, recall, and F1-Score and that is 99% in both of the approaches. Now, if we look into the approach 1 results where all features are used, it can be seen that there are also two more classifiers that achieved the same evaluation scores as Random Forest. The classifiers are KNN and LightGBM. However, when top-10 features are only used, the performance of these models decreases a little. KNN achieves an accuracy of 96% and

LGBM achieves 97% accuracy compared to the 99% accuracy of approach 1 of both classifiers. But these classifiers still perform better than the other classifiers of the research. The lowest performance is noticed by the Multi-layer perceptron model in approach-1 which is 71% of accuracy and 62% recall and 61% of F1-score. Nevertheless, the interesting factor is the performance of this classifier increases when only top-10 features are used. The accuracy, recall, and F1-score get increased to 95%, 94%, and 95% respectively which is a satisfactory increase. However, the precision of the MLP model is adequate in both of the approaches. All other classifiers like LR, SVC, DT, and AdaBoost also show satisfactory results in both of the approaches with all having accuracy above 90%.

We can see the accuracy comparison on the train set and test set for both of the approaches in figure 6 and figure 7. It is also evident from the graph that, RF, KNN, and LGBM are the top-3 best-performing classifiers in both approaches. They achieved 99% accuracy in both the train and test sets of approach -1. MLP however performed better in the training set compared to the test set in both of the approaches.

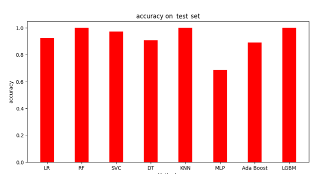


(a) All Features

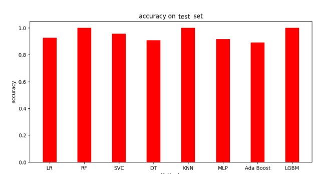


(b) Top 10 Features

Fig. 6: Training Accuracy of Models



(a) All Features

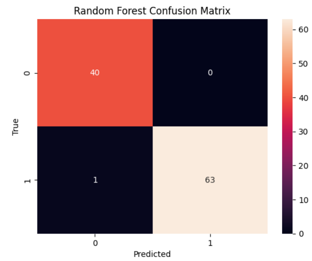


(b) Top 10 Features

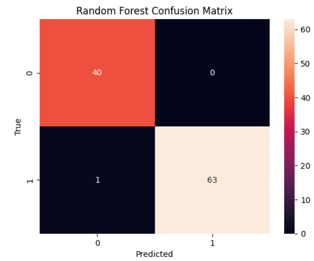
Fig. 7: Testing Accuracy of Models

From the confusion matrix of the best and worst performing models, we can get an in-depth idea about the strong and weak aspects of the model performance. From figure 8 we can see that, the Random Forest classifier correctly classifies all of the healthy classes (40) correctly and misclassifies only one diabetic patient to the healthy class in both of the approaches. For KNN in figure 9, the scenario is just the opposite where the classifier correctly predicts all of the diabetic classes correctly but fails to predict one healthy class accurately in approach-1. In approach-2, KNN misclassifies 3 diabetic patients as healthy patients.

In the LightGBM classifier confusion matrix in figure 10 we can see that, LGBM misclassifies only one data of the diabetic class in approach-1 and three data of the diabetic

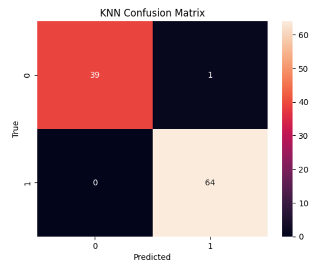


(a) All Features

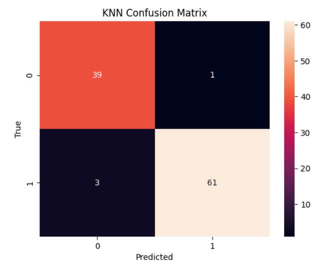


(b) Top 10 Features

Fig. 8: Random Forest Confusion Matrix



(a) All Features



(b) Top 10 Features

Fig. 9: KNN Confusion Matrix

class in approach-2. But it classifies all of the healthy data points accurately in both of the approaches. Now coming to the lowest performing classifier MLP which is shown in figure 11, it accurately predicts all of the diabetic data points but fails to predict 30 healthy data points among 40 data in approach-1. It somehow labels all of the healthy classes as the diabetic class which is the reason for the worst performance of the classifier. In approach-2, the performance gets better when only 5 healthy patients are predicted as diabetic patients.

In summary, in a field like early diabetes detection, it is crucial that a prediction model is able to identify accurately the diabetic patients compared to the healthy patients. As identifying diabetic patients as healthy patients can cause many more complications and mistreatment in the medical sector. In a field like this, it is essential that the precision and f1-score are taken more into account than just the accuracy. We could see that despite performing poorly with accuracy, the precision is always up to the mark for the MLP model. And of course, all of the classifiers have satisfactory precision and F1-score whereas the best-performing models achieved 99% precision, recall, and F1-score.

VI. Conclusion and Future Works

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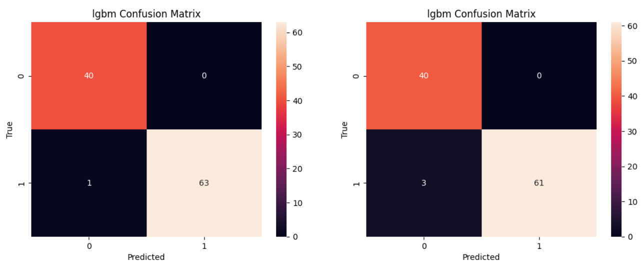
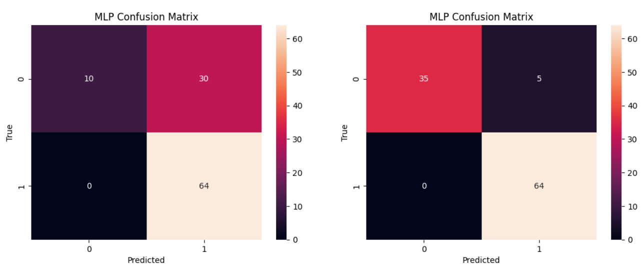
TABLE II: Results on Test Data.
Here, Approach 1 - Using All Features and Approach 2 - Using Top-10 Features

Model	Accuracy(%)		Precision(%)		Recall(%)		F1-Score(%)	
	Approach 1	Approach 2	Approach 1	Approach 2	Approach 1	Approach 2	Approach 1	Approach 2
Logistic Regression	96	95	96	95	96	95	96	95
Random Forest	**99**	**99**	**99**	**99**	**99**	**99**	**99**	**99**
SVC	97	96	97	96	97	96	97	96
Decision Tree	93	93	93	93	93	93	93	93
KNN	**99**	96	**99**	96	**99**	96	**99**	96
MLP	71	95	84	96	62	94	61	95
AdaBoost	90	90	91	91	89	89	90	90
LGBM	**99**	97	**99**	97	**99**	98	**99**	97



(a) All Features (b) Top 10 Features

Fig. 10: LGBM Confusion Matrix



(a) All Features (b) Top 10 Features

Fig. 11: MLP Confusion Matrix

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