

## **AI-Driven Early Detection of Diabetes: A Machine Learning Approach**

**Sudha Rani<sup>1\*</sup>, Nethravathi B<sup>2</sup>**

<sup>1</sup>Student, M. Tech in Data Science, Department of Information Science and Engineering,  
JSS Academy of Technical Education, Bengaluru, Karnataka, India

<sup>2</sup>Associate Professor, M. Tech in Data Science, Department of Information Science and  
Engineering, JSS Academy of Technical Education, Bengaluru, Karnataka, India

**\*Corresponding author**

**Email Id:- sudharani7887@gmail.com**

### **ABSTRACT**

*Diabetes is regarded as among the most deadly and chronic diseases and is brought on by an increase in blood sugar levels. If it is left untreated or undiagnosed, numerous consequences may arise. A patient is forced to visit a diagnostic facility and consult a physician put down to the time-consuming identification process. However, the advancements in ML methods solve this important issue. Acquiring a model that can tell a patient's likelihood of acquiring diabetes is the objective of this study. Thus, to identify diabetes early on, this experiment uses five machine learning classification algorithms: Random Forest, K-Nearest Neighbor, SVM, Decision Tree, and Logistic Regression. Tests are conducted using the Bangladesh Diabetes Dataset (BDD), which comes from the Kaggle machine learning library. Several metrics, including precision, accuracy, and recall, are used to estimate the performance of these approaches. Accuracy is computed by comparing cases that were correctly and wrongly classified. When correlated to the algorithm for logistic regression, Random Forest performs better, with a High accuracy of 96%.*

**Keywords:-** Decision Tree, Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbours Diabetes, Random Forest

### **INTRODUCTION**

The absence of the hormone insulin results in diabetes mellitus, often known as diabetes, one of the chronic disorders that cannot be cured. The pancreas produces this vital hormone, which enables cells to take up glucose, or blood sugar, from dietary sources to give them the energy they need. According to medical terminology, hyperglycemia is the state where blood sugar levels are high.

Two primary causes of this condition include the body's inability to produce the insulin needed by the blood cells and its inability to react appropriately to insulin. If the body is unable to use glucose to generate energy, it accumulates in the

blood, which leads to hyperglycemia. The body requires insulin in order for blood glucose to reach the cells and be used as energy.

According to estimates from WHO or the World Health Organization, diabetes claims the lives of roughly 1.6 million people annually. Insulin shortage is the outcome of type 1 diabetes, which is brought on by the Auto immune diabetes mellitus. Type 2 diabetes is largely a result of insulin resistance, diabetes from specific other causes, and Gestational Diabetes Mellitus, which is diabetes diagnosed in mid-to-late pregnancy, is the general categorization of diabetes.

Type 2 diabetes is the most common type of the disease. (T2DM) [1]. The latest report from the Global Diabetes League (2019) estimates that the prevalence of diabetes will reach 9.3% worldwide, affecting 463 million people [3]. According to medical professionals and recent studies, the likelihood of recovery is higher if the illness is identified early prediction has benefited greatly from the use of machine learning and deep learning tactics and illness analysis as a calculation of the ongoing advancements in technology.

This study uses a number of different methods to predict diabetes, including Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Decision Tree, Random Forest (RF), and Logistic Regression. Implementing machine learning and deep learning tactics to predict diabetes has been the topic of numerous recent studies. For example, writers have used the Deep Neural Network (DNN) technology to offer a deep learning-based approach for diabetes data categorization.

The Pima Indians Diabetes data set was used to test the suggested system. Using Random Forest, the suggested system demonstrated good classification accuracy, precision, and recall. Immune systems are weakened in those with type 1 diabetes, and their cells are unable to create adequate insulin. There is now no convincing study proving the causes of type 1 diabetes, and there is no effective prophylactic interventions. Either inadequate insulin synthesis by the cells or inappropriate insulin use by the body are the hallmarks of type 2 diabetes. This kind of diabetes is the most common and affects 90% of people with the disease. It is caused by both genetic factors and lifestyle decisions. Type 3 Gestational diabetes is one kind of diabetes that develops during pregnancy. Gestational diabetes is frequently diagnosed between weeks 24 and 28 of pregnancy.

Diabetes testing necessitates hospital visits when blood samples must be taken and findings must be obtained after a lengthy wait. As an alternative, diabetes may also be detected by a urine test, but the process is the same. We have created a model that uses a person's symptoms to identify diabetes. In this model, sixteen symptoms that a diabetic might experience are considered. We may determine if a person has diabetes by using these symptoms as input.

In addition to having all the essential information on medications, dietary practices, and preventative measures, we have developed a platform that allows individuals to check for early-stage diabetes detection without having to visit hospitals. Early identification and prevention, individualized treatment options, better patient outcomes, disease monitoring, and resource allocation are some benefits of diabetes prophecy using ML models. Individuals can lower their chance of acquiring diabetes by changing their lifestyle or taking medication with the aid of early identification and prevention.

## **LITERATURE REVIEW**

Oana Virgo Lici and Bogdana Virgo Lici's (2024) utilize ML models to forecast diabetes and its complications are examined in Machine Learning Tactics for Diabetes Prediction. It highlights the challenges in determining the best prediction models due to differences in databases, data preprocessing, and algorithms used across studies.

The objective is to give a summary of the many machine-learning models used to predict diabetes. Reviewing around 60 studies. These studies mostly use public datasets like the Pima Indians Diabetes Dataset (PIDD) and local data. The paper does not conduct original data analysis but compares the results from different models and discusses their performance. The

authors conclude that no single model stands out as the best due to the variations in research methods, but improving collaboration between medical professionals and computer scientists could lead to better prediction tools for diabetes [1].

Modak and Jha (2023) used ensemble methods and ML algorithms to produce a diabetes prediction model. They assessed models using accuracy and AUC-ROC ratings on a real-world dataset from Kaggle. With an AUC-ROC score of 0.99 and accuracy of 95.4%, Correlate to the other approaches, Cat Boost fared better. The study emphasizes how ensemble learning can increase prediction accuracy. Their research provides a solid basis for diagnosing diabetes early [3].

De, T. K., Likhitha, P., Vamsi, J., Sai, T. K., Jaswanth, S., Teja, N. S. K., & Raju, P. N. (2024). Created a diabetes prediction model for early rectification and treatment. To determine risk, the study examines clinical, lifestyle, and demographic variables. Data reprocessing, feature engineering, model creation, and evaluation are all included in a structured framework. Ethical aspects like data privacy are prioritized. The development shows how well ML Algorithms predict diabetes. The study provides both individuals and healthcare professionals with a useful tool.[2]

Hosam El-Sofany et al. (2023) A machine learning-based method for diabetes prediction that handles imbalanced data by utilizing a semi-supervised model, gradient boosting, and SMOTE. The study focuses on Saudi Arabia using a proprietary dataset of 300 samples and the Pima Indians Diabetes Dataset. XGBoost was the more precise of the ten classifiers that were tested (97.4% for the private dataset and 83.1% for the combined datasets).

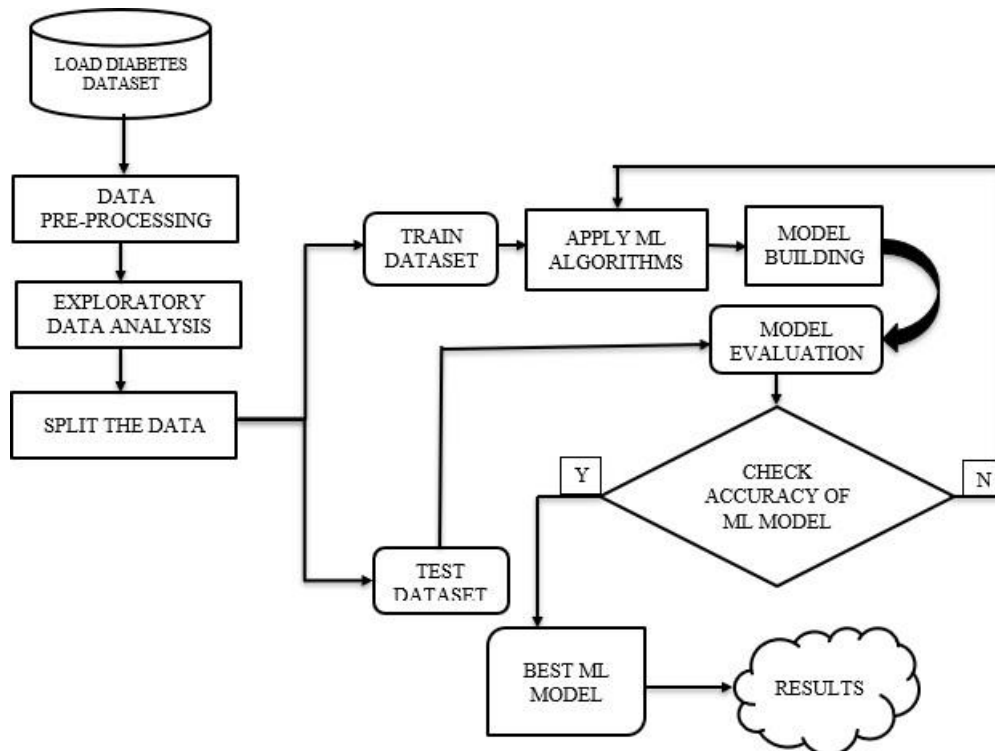
A smartphone app for real-time diabetes prediction was created, and feature importance was interpreted using Explainable AI (SHAP). According to the study's findings, the suggested methodology improves diabetes management and healthcare outcomes by enhancing early identification [4].

Elmenshawy et al. (2022) used a new dataset from Bangladesh with the Pima Indian dataset to create a diabetes machine learning-based prediction model and explainable AI approaches. They used SMOTE and ADASYN to handle class imbalance and implemented tactics. like Decision Trees, Logistic Regression, and XGBoost. With a stacking strategy, they were 99.3% accurate. The potential of cutting- edge approaches for early diabetes identification and better healthcare outcomes as illustrated by the use of explainable AI methods, including SHAP and LIME, for model interpretability [5].

Xue, Min, and Ma (2020) concentrated on predicting diabetes using machine learning, particularly type 1 diabetes, which frequently exhibits mild symptoms. They used data from 520 people with diabetes and those at risk for developing the disease to apply SVM, Naive Bayes, and Light. SVM performed the best in the study's search for the most accurate prediction model. The study emphasizes the importance of early detection in avoiding long-term problems from diabetes [6].

## **METHODOLOGY**

To anticipate the model, we are employing the below stages. Load diabetes dataset, Preprocessing data, training, and test datasets, implement algorithms, assess the model, and identify the optimal model It offers excellent accuracy and results when determining if a person has diabetes; if so, it indicates that the person has the disease; if not, it indicates that they do not.



*Fig.1:-The suggested method's sequences for diabetes prediction*

## INFORMATION GATHERING

This module covers gathering and analyzing data in order to identify patterns and trends that aid in forecasting and assessing outcomes. Direct questionnaires from Sylhet Diabetes Hospital patients in Sylhet, Bangladesh, were employed, with a doctor's approval, to collect this data.

The collection contains several characteristics of 521 patients. There is one goal value and sixteen characteristics in this dataset. The outcome is the characteristic that we will forecast: "0" is negative and "1" is positive. The dataset's features are explained below Age: Age, expressed in years, from 20 to 65

1. Gender: either female or male
2. Yes/No for polyuria
3. Yes/No for polydipsia
4. Yes/No for sudden weight loss
5. Yes/No for weakness
6. Yes/No for polyphagia
7. Yes/No for genital thrush
8. Yes/No for visual blur
9. Yes/No for itching

10. Yes/No for irritability
11. Yes/No for delayed healing
12. Yes/No for partial paresis
13. Yes/No for muscle stiffness

## DATA PREPROCESSING

In healthcare data analysis, data preparation is an essential step that guarantees better data accuracy and quality. It assists in handling missing values, eliminating inconsistencies, and optimizing the dataset for improved model performance. The process of data cleaning entails eliminating extraneous characteristics, duplicate entries, and missing information.

Additionally, it entails changing data types and removing instances of zero values since they are invalid. Through dataset refinement, data cleaning guarantees that only pertinent and significant information is kept. Data processing, this step converts the dataset into an analysis-ready format after it has been cleaned.

### EXPLORATORY DATA ANALYSIS

Each column's association matrix was created during the exploratory data analysis phase. Box plots and other visualizations were created to look for outlier values. To explore the connection between the label column and the features, additional visualization was also carried out. An important step in this process is feature selection, where the primary features for the model are chosen, and the data is fitted to the model to generate predictions.

### DATA SPLITTING INTO TEST AND TRAINING DATA SET

To evaluate model performance in machine learning, data must be diverged into train and test sets. While the model's capability is assessed by the testing set to predict unseen data, the model learns using the training set by finding patterns in the data. However, it might change according to the size of the dataset and the needs of the model a typical split ratio is 75% for training and 25% for testing. This method guarantees that the model generalizes effectively to new data and helps avoid over-fitting.

A random state of 38 is used to guarantee consistency in the split across several runs, and 25% of the dataset is left aside for testing. The training dataset is subjected to SMOTE (Synthetic Minority Over-sampling Technique) to address class

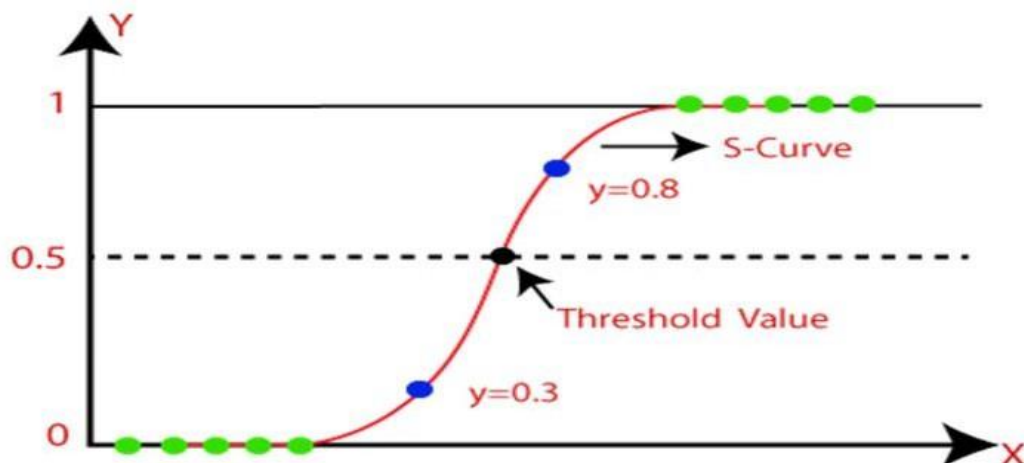
imbalance. By guaranteeing a balanced dataset, SMOTE improves model performance by producing synthetic examples for the minority class. This method preserves a fair assessment of the unaltered test data while improving classification accuracy

### MODEL BUILDING

**Model Construction:** This is the most crucial stage, which involves developing a diabetes prediction model. In order to forecast diabetes, the model has applied several machine-learning techniques. The following are some of these algorithms: Random Forest, Ada Boost, K-Nearest Neighbour, Decision Tree, Extra Tree, Support Vector, Perceptron, Linear Discriminant Analysis, and Logistic Regression [8]

#### Logistic Regression

Logistic regression analysis, under the heading of supervised learning, the nominal dependent variable is predicted using a specific set of independent factors. The outcome of a nominal dependent variable is predicted via logistic regression. LR uses an S-curve rather than a straight line to match the points so that addresses categorization issues. There should be no multi-collinearity in the independent variable.



*Fig.2:-Logistic Regression*

**a. Decision Tree**

The decision tree, which resembles a flowchart and has internal nodes that describe tests on attributes, branches that describe test results, and leaf nodes (terminal nodes) that hold class labels, is the most popular and efficient tool for classification and prediction. It handles high-dimensional data, and its classifiers often achieve high accuracy. Decision tree learning, also known as induction of decision trees, is part of the predictive modeling approaches used in statistics, data mining, and ML models.

**b. Random Forest**

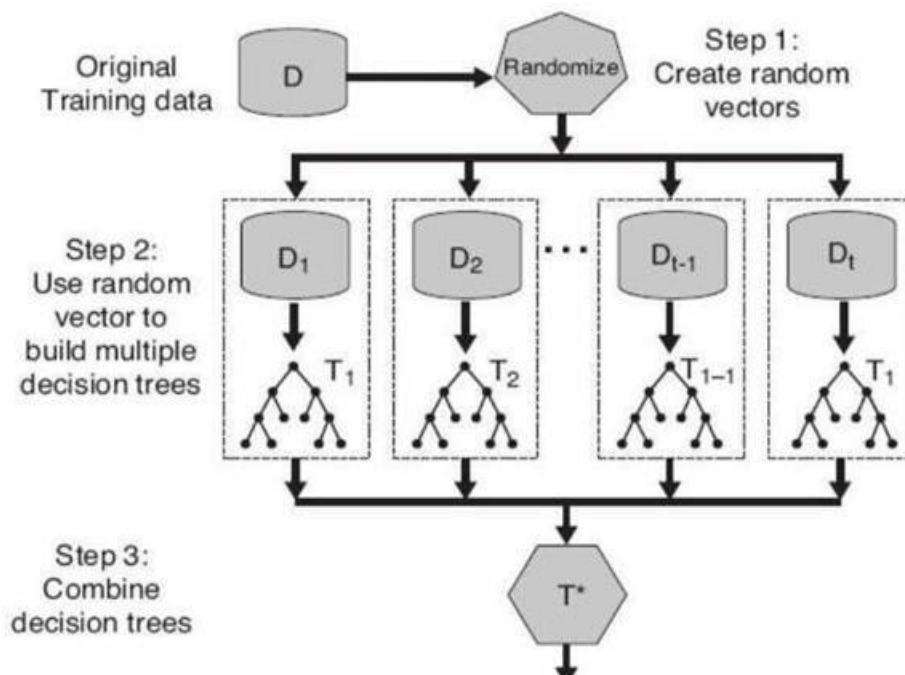
Numerous decision trees are assembled in the time training, and the class that emerges is either the mode of the classes (classification) or the mean prediction (regression) of the single trees. Random decision forests are ensemble methods for classification, regression, and other problems.

The tendency of decision trees to overfit their training set is compensated for by random decision forests. Mark that constructing the forest is not identical to

making the decision contingent on the information gain technique or the gain index. If you give the decision tree a training dataset with targets and features, it will generate a set of rules. Predictions can be made using these rules.

**Random Forest's benefits include:**

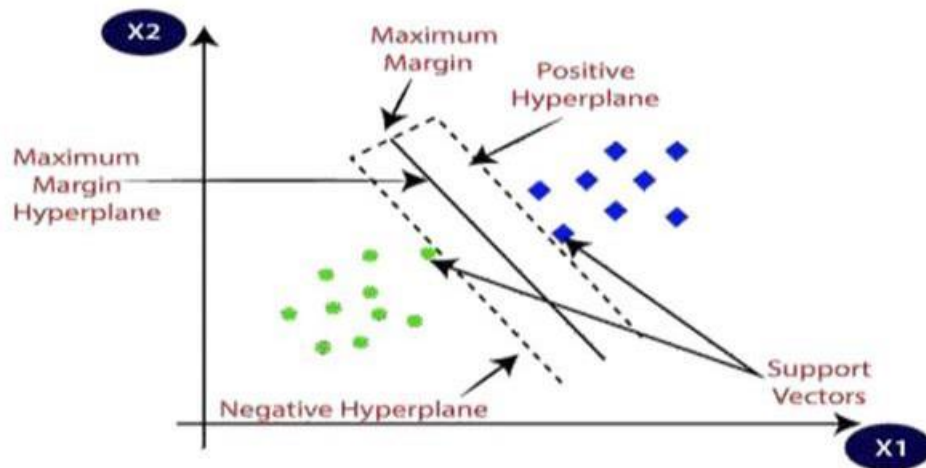
1. Random forests are capable of solving both classification and regression problems, and They provide accurate estimations in both areas.
2. Random Forest's major advantage is it has the potential to manage large data sets with increasing dimensionality. It can take hundreds of input variables and determine the most significant variables, making it a dimensionality reduction strategy. A very helpful feature of the method is that it also generates the variable's importance.
3. A successful tactic for predicting absent values allows it to maintain accuracy even when a bulk of the data is missing.
4. It contains techniques for balancing mistakes in data sets with unequal class distributions.



**Fig.3:-Random Forest**

**c. Support Vector Machine**  
SVM's principal target is to determine which hyperplane best separates the data into classes. Supervised learning is used by SVM, a generalized linear classifier, to categorize binary data. The maximum-margin hyperplane for solving learning samples serves as its decision boundary. Both linear and nonlinear datasets can be

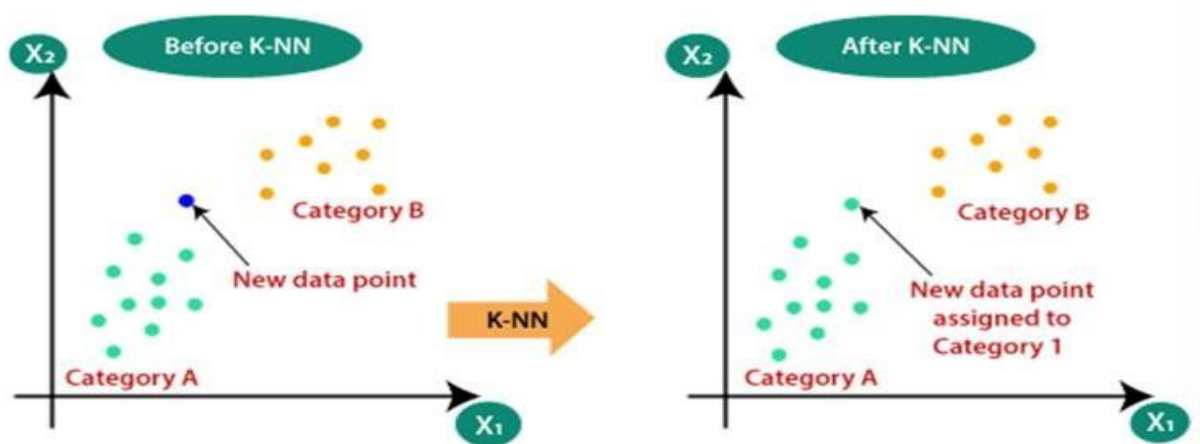
handled by SVM with the use of many kernel functions, such as linear, polynomial, radial basis function (RBF), and sigmoid. SVM optimizes structural risk by adding a regularization term to the solution system and calculating empirical risk using the hinge loss function. SVM has good classification skills, particularly when a lot of features are included.



*Fig.4:-Support Vector Machine*

**d. K-Nearest Neighbour**  
It utilizes the labels of the  $k$  training set data points that are closest to a given input data point to generate a prediction. Numerous distance metrics, including the Manhattan, Minkowski, and Euclidean distances, can be used to calculate the separation between data points. Methods such as cross-validation can be applied to find the ideal value of  $k$ , and the bias-variance trade-off

may be impacted by the choice of  $k$ . KNN variants include KNN with kernel functions, which apply a kernel function to the distance metric, and weighted KNN, which assigns greater weight to closer neighbors. Preparing and preprocessing the data, figuring out the distances between data points, and applying the algorithm to make predictions are all part of putting.



*Fig.5:-K-Nearest Neighbour*

## EVALUATING MODEL

The process of evaluating a model helps determine its accuracy and predictive power. There are a handful of approaches for estimating a model, and the method used will depend on the type of issue and the data being utilized. This is the procedure for evaluating its performance on a given task using a collection of evaluation measures. After training, evaluate the machine learning model's performance using the testing data by

calculating metrics such as recall, accuracy, and precision.

**Confusion Matrix:** In machine learning and statistics, a confusion matrix is a performance evaluation tool used to gauge a classification model's accuracy. A confusion matrix is also identified as a square matrix that compares the actual labels of the data sets with the model's predictions to provide a summary.

a) **Accuracy:** The percentage of cases that were properly categorized among all the situations

$$(TP + TN) / (TP + TN + FP + FN) = \text{accuracy.}$$

TP: "True Positive." TN: "Actual negatives" FN: "False Negatives" FP: "False positives"

b) **Precision:** For all predicting positive cases (Tp + Fp), it is meant to be the measure of correctly recognized positive cases (Tp).

$$TP / (TP + FP) = \text{Precision}$$

c) **Recall:** It is inferred to be the percentage of accurately detected positive cases (Tp) among all positive instances.

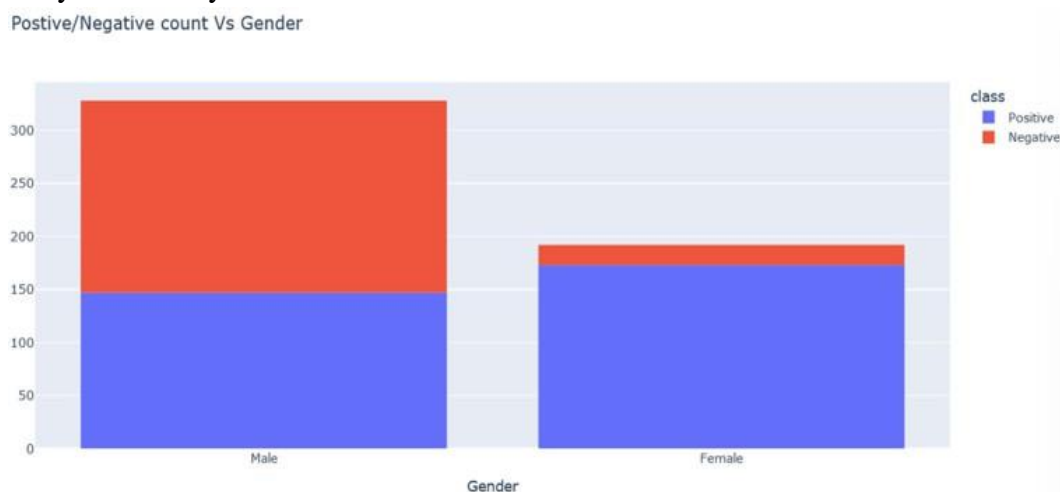
$$TP / (TP + FN) = \text{Recall}$$

## RESULTS

Five distinct machine learning algorithms support vector machine, k-nearest neighbour, random forest, decision tree, and logistic regression were deployed to a dataset representing diabetes symptoms as

features for the early-stage diabetic prediction project. Once we assessed these algorithms' performance, we discovered that the random forest approach yielded the best accuracy and precision, 95.51% and 0.961905, respectively.

### Exploratory Data Analysis Gender Distribution

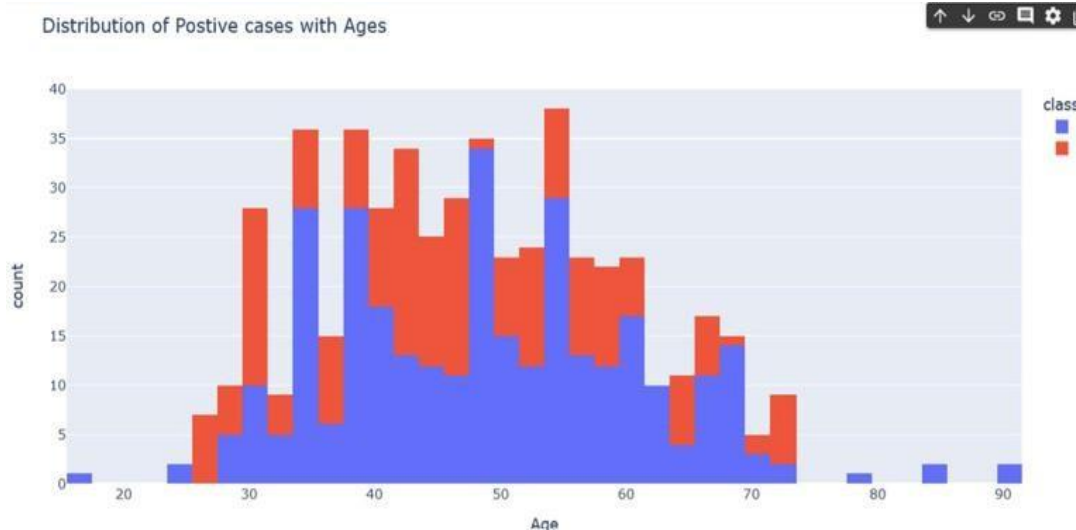


**Fig.6:-** With Positive and Negative Class Gender Distribution

class	Negative	Positive
Gender		
Female	9.500000	54.060000
Male	90.500000	45.940000

*Fig.7:-Process of EDA*

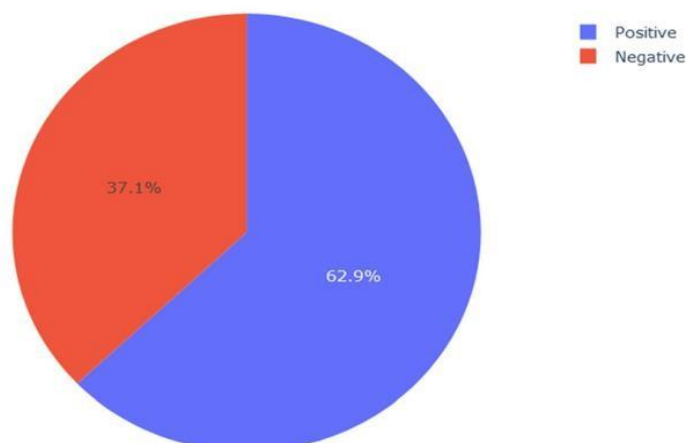
### Distribution of Positive cases with Ages



*Fig.8:-With positive and negative class Age distribution*

### Distribution of cCass (Target Variable)

Ratio of Positive and Negative cases

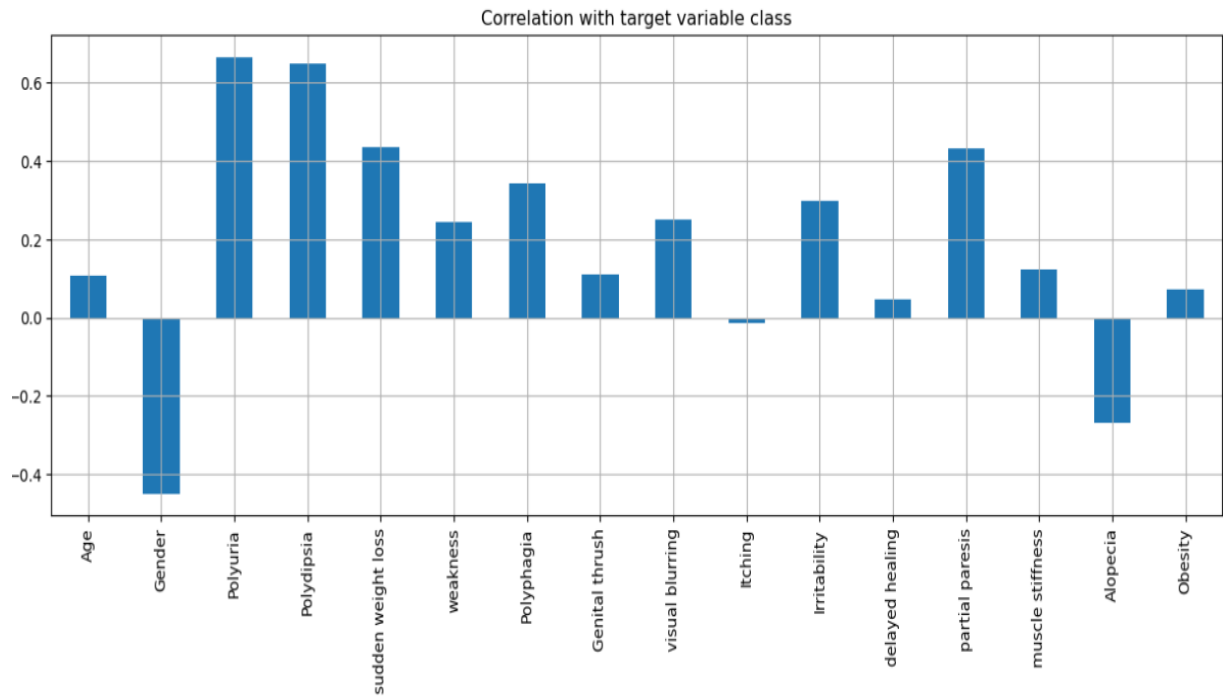


*Fig.9:-Distribution of target variable*

### Correlation of Data

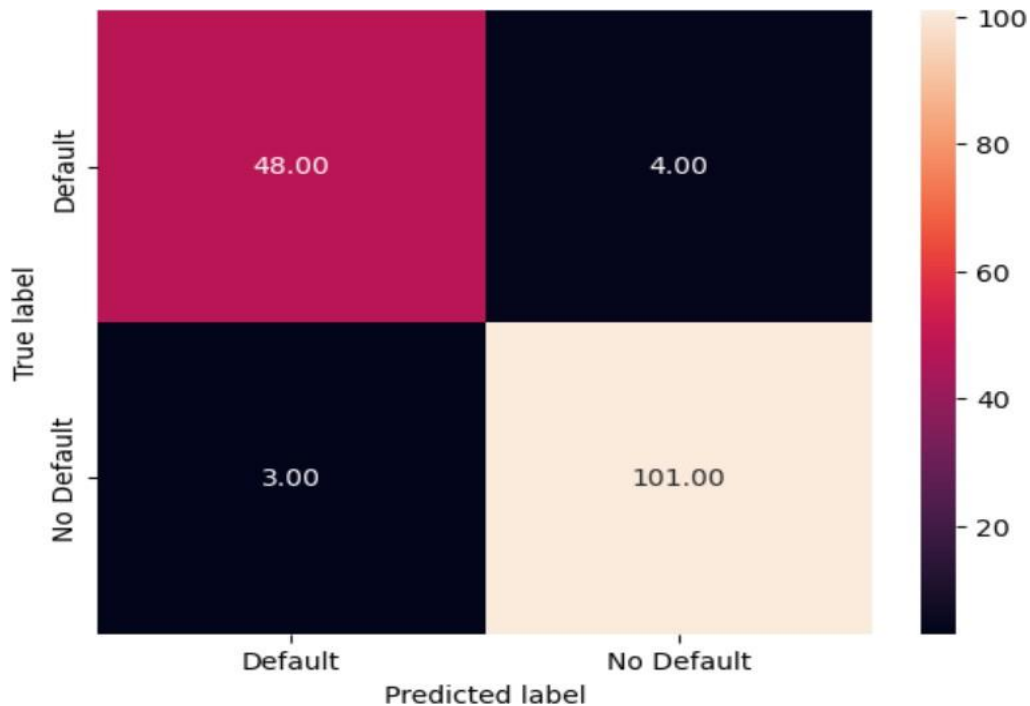
Data correlation is the strength and direction of the association between two or more variables in a dataset. Correlation measures the association degree among two variables and ranges from -1 to 1,

where 0 indicates no correlation. One variable increases along with the other when there is a positive correspondence between them, and the other variable decreases, which shows a negative correlation.



*Fig.10:-Correlation graph*

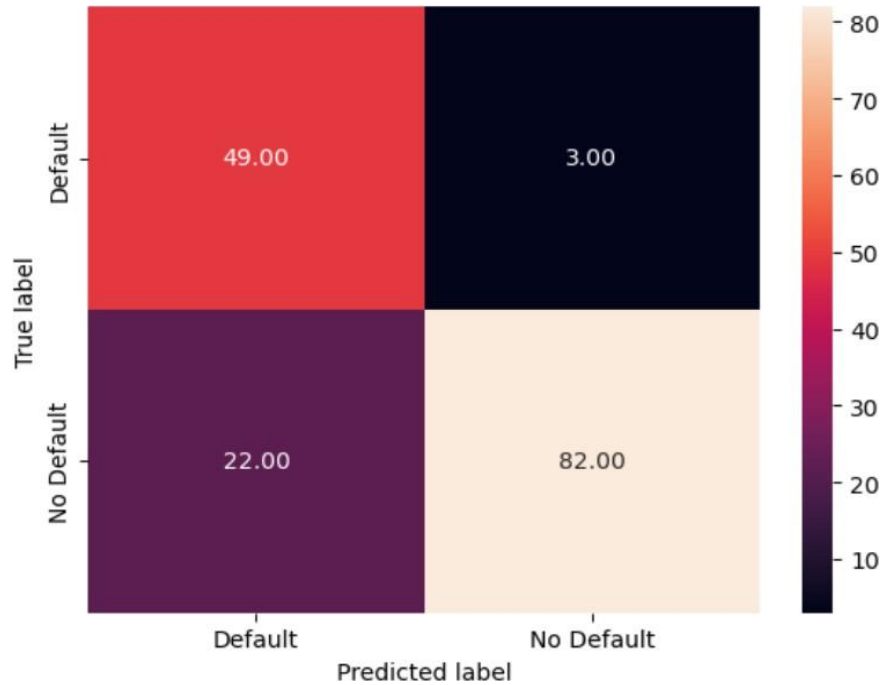
### Random Forest



*Fig.11:-Confusion Matrix of RF*

Confusion Matrix in Fig. 3: True Positive 48% 101% True Negative 4% of cases are false positives. False Negative 3%.

### Support Vector Machine (SVM)



**Fig.12:-confusion matrix of SVM**

Confusion Matrix in Fig. 4: 49% True Positive 82% True Negative 3% of 7 False Positives False Negative.

**Table 1: Analysis of Results**

Algorithm	Accuracy	Precision	Recall
Random Forest	95.51	0.971154	0.961905
KNN	83.97	0.788462	0.964706
Decision Tree	95.51	0.955128	0.955128
Support Vector Classifier	91.67	0.916667	0.916667
Logistic Regression	94.87	0.948718	0.948718

The following table of contents shows that decision trees and random forests provide the greatest accuracy out of all the methods. Thus, we consider the next two

characteristics to choose the best course of action. Because random forest offers the highest precision and recall, we employ it to achieve the best outcomes.

## CONCLUSION & FUTURE SCOPE

The Early-stage Diabetic Prediction System is an all-inclusive tool that uses machine learning tactics to forecast an individual's chance of developing diabetes relying on their symptoms. The system analyses a collection of diabetes symptoms using a number of machine-learning algorithms to identify patterns and associations between the symptoms and the likelihood of developing the condition.

To provide a seamless user experience, a unique platform for diabetic diseases has been created. It contains a variety of information, including specifics on the various forms of diabetes, the medications that are prescribed, and health advice. Through this platform's internet interface, users may access information at any time and from any location.

People may access relevant information and resources while estimating their risk of developing diabetes problems using the Future Scope System and its associated portal. Diabetes is acquired by machine learning techniques. By empowering individuals to take control of their health, we hope to improve their overall well-being and quality of life. In diabetes prediction, machine learning may also save healthcare costs by promoting early disease identification and prevention. By determining who is most likely to develop diabetes and following preventative measures, medical personnel can help delay or even prevent the start of the disease.

## REFERENCES

1. Oana Virgolici, Bogdana Virgolici. Diabetes Prediction Using Machine Learning Techniques: A Brief Overview. Diabetes Complications. 2024; 8(1); 1-9. Journal of Computational Intelligence in Bioinformatics:1-8.
2. Tushar Kanti De1, Prathipati Likhitha2, J Vamsi3, T Krishna Sai4, S Jaswanth5, N Sai Krishna Teja6, P Narasimha Raju7 Diabetes Prediction using Machine Learning March 2024 International Journal of Advanced Research in Computer and Communication Engineering,1(13).
3. Modak, S.K.S., Jha, V.K. Diabetes prediction model using machine learning techniques. *Multimed Tools Appl* **83**, 38523–38549 (2023). Multimedia Tools and Applications (2024) 83:38523–38549 <https://doi.org/10.1007/s11042-023-16745-4>.
4. HosamEl-Sofany and IslamA.T.F.Taj-Eddin, SamirA.El-Seoud , OmarH.Karam, Yasser M. Abdel-Latif” A Proposed Technique Using Machine Learning for the Prediction of Diabetes Disease through a Mobile App” December 2023 Hindawi International Journal of Intelligent Systems Volume 2024, Article ID 6688934, 13 pages <https://doi.org/10.1155/2024/6688934>.
5. Isfafuzzaman Tasin, Tansin Ullah Nabil, SanjidaIslam, RiasatKhan Diabetes prediction using machine learning and explainable AI techniques 2022 DOI: 10.1049/htl2.12039.
6. Jingyu Xue1st,a, Fanchao Min2rd,b, Fengying Ma3nd,c\* Research on Diabetes Prediction Method Based on Machine Learning 202 Journal of Physics: Conference Series 1684 (2020) 012062. IOP Publishing doi:10.1088/1742-6596/1684/1/0120620.
7. Mitushi Soni Dept of Computer Science and Engineering Shri G.S. Institute of Technology and Science Indore, India, Dr. Sunita Varma Dept of Information Technology Shri G.S. Institute of Technology and Science Indore, India Diabetes Prediction using Machine Learning Techniques 2020.
8. Aishwarya Mujumbara, Dr. Vaidehi Vb Diabetes Prediction using Machine Learning Algorithms 2019 DOI:[10.1109/ICACCS51430.2021.9441935](https://doi.org/10.1109/ICACCS51430.2021.9441935) Conference: 2021 7th International

- Conference on Advanced Computing and Communication Systems (ICACCS).
9. M. .F. Faruque. Asaduzzaman and I. H. Sarker, 'Performance Analysis of Machine Learning Techniques to Predict Diabetes Mellitus,' 2019 International Conference on Electrical, Computer 3IId Communication Engineering (ECCE), 2019, pp. 1-4, doi: 10.1109/ECACE.2019.8679365.
  10. M. A. Sarwar, N. Kamal, W. Hamid, and M. A. Shah, "Prediction of Diabetes Using Machine Learning Algorithms in Healthcare," 2018 24th International Conference on Automation and Computing (ICAC), 2018, pp. 1-6, doi: 10.239 19/IC on A C./O18.87489 92.
  11. D. Shetty, K. Rit, S. Shaikh and N. Patil, "Diabetes disease prediction using data mining," 2017 International Conference on Innovations in Information, Embedded 3IId Communication Systems (ICIIECS), 2017, pp. 1-5, doi:10.1109nCIIECS.2017.8276012.
  12. Choubey, D.K., Paul, S., Kumar, S., Kumar, S., 2017. Classification of Pima indian diabetes dataset using naive bayes with genetic algorithm as an attribute selection, in: Communication and Computing Systems: Proceedings of the International Conference on Communication and Computing System (ICCCS 2016), pp. 451–455.
  13. Miguel Villagómez Galindo , Ana Beatriz Martinez Valencia , Bindiya M K, Nethravathi B, Sudhanshu Maurya , Sai Sudha Gadde, Anand Khandare , Veerendra D, "Advanced Direction-of-Arrival Estimation in Coprime Arrays via Adaptive Nyström Spectral Analysis", IEEE Sensors Letters, ISSN: 2475-1472 (Online) Vol.8, No.2 February 2024, DOI: 10.1109/LENS.2024.3349651.
  14. Sahana V, Nagamani H Shahapure, Rekha P M, Nethravathi B, Pratiksha Khandelwal, Abhinav Anand, Pranjal Agrawal, Vedant Srivastava, "The DistilBERT Model: A Promising Approach to Improve Machine Reading Comprehension Models", International Journal on Recent and Innovation Trends in Computing and Communication, ISSN: 2321-8169 Volume: 11 Issue: 8 DOI: <https://doi.org/10.17762/ijritcc.v11i8.7957> , pp. 293-309, 2023.
  15. Nethravathi B, Srinivasa H P , Hithesh Kumar P , , Amulya S , , Bhoomika S , , Banashree S Dalawai,, Chakshu Manjunath, "Visually Impaired Person Assistance Based on Tensor FlowLite Technology", International Journal of Advanced Computer Science and Applications, Volume 13, Issue No. 11, NOV 2022, pp. 609-614. SJR 0.28 Doi:10.14569/issn.2156-5570.
  16. Anil. B.C., Dayananda P, Nethravathi B and Raisinghani, M.S(2021), Efficient Local Cloud-Based Solution for Liver Cancer Detection using Deep Learning, International Journal of Cloud Applications and Computing, IGI Global. Volume 12, Issue 1, article 9, page no.1-13, Jan 2022 DOI: 10.4018/IJCAC.2022010109.
  17. Mohammed Tolha Baig, Nethravathi B, "A Deep Learning Strategy For Effectively Detecting Small Faces In Challenging Images" at International Journal of Engineering Applied Sciences and Technology, Vol. 9, Issue 01, ISSN No. 2455-2143, Pages 64-70, May 2024. DOI: [10.33564/IJEAST.2024.v09i01.008](https://doi.org/10.33564/IJEAST.2024.v09i01.008).
  18. Shoury Verma, Vaibhav Saini , Vivek Kumar Singh , Nethravathi B, "Advancements in Semantic Segmentation: A Comprehensive Review and Comparative Analysis of Fully Convolutional Networks (FCN)", at International Research Journal of Modernization in Engineering Technology and Science, e-ISSN: 2582-5208, Volume 6 Issue 1, January 2024 <https://www.doi.org/10.56726/IRJMETS>

- [48360](https://www.doi.org/10.56726/IRJMETS48360).
19. Pravallika N , P Sneha , Radhika V , Nethravathi B, “STUDY ON DIFFERENTIAL PRIVACY WITH MACHINE LEARNING” at International Research Journal of Modernization in Engineering Technology and Science, e-ISSN: 2582-5208, Volume 6 Issue 1, January 2024 <https://www.doi.org/10.56726/IRJMETS48565>.
20. Sreeranga J , Vishal K T , Sudarshan N , Nethravathi B, “Leveraging Feedforward Neural Networks for Image Processing: An Overview and Analysis”, at International Research Journal of Modernization in Engineering Technology and Science, e-ISSN: 2582-5208, Volume 6 Issue 1, January 2024, <https://www.doi.org/10.56726/IRJMET48563>.
21. Priyanshu Mishra , Prathamesh Katkam, Ankith Bhargav , Srinivasan N , Nethravathi B, “Unleashing the Power of Artificial Intelligence: A Comprehensive Exploration of OpenAI”, at International Research Journal of Modernization in Engineering Technology and Science, e-ISSN: 2582-5208, Volume 6 Issue 1, January 2024. <https://www.doi.org/10.56726/IRJMET48603>.
22. Vishnu B V, Sharath S Rao, Nethravathi B, “AN INTERACTIVE FRAMEWORK FOR QUERYING DATA FROM LARGE PDF FILES”, 2023, International Conference on Recent Advances in Information Technology for Sustainable Development (ICRAIS), Date of Conference: 06-07 November 2023, MAHE, Manipal, INDIA Date Added to IEEE Xplore: 27 December 2023, DOI: 10.1109/ICRAIS59684.2023.10367090.
23. Sneha T, Nethravathi B, Nagamani H Shahapure, Nagashree S, Sinchana S Shashidhara, "Future Agriculture Farm Management Using Augmented Reality: A Study," 2022 Fourth International Conference on Cognitive Computing and Information Processing (CCIP), Bengaluru, India, 2022, pp. 1-4, doi: 10.1109/CCIP57447.2022.10058665. March 2023.
24. Abhilash Karri, Sharath S. Rao, D. V. Ashoka, Nethravathi B, Sahana V and Vishnu B. V, "Hardware Inventory Management System Using IoT," 2022 Fourth International Conference on Cognitive Computing and Information Processing (CCIP), Bengaluru, India, 2022, pp. 1-4, doi: 10.1109/CCIP57447.2022.10058647. March 2023.