GLUCOTRACK: AI-POWERED DIABETES RISK PREDICTION ON IOT

A DESIGN PROJECT REPORT

Submitted by

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K. RAMAKRISHNAN COLLEGE OF TECHNOLOGY (AUTONOMOUS)

SAMAYAPURAM – 621 112

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BONAFIDE CERTIFICATE

Certified that this Design project report titled **"GLUCOTRACK: AI-POWERED DIABETES RISK PREDICTION ON IOT"** is the Bonafide work of **SRUTHI S (811720243044), ABINAYA M (811720243002), AATHYUKTHA S (8117202430001)**, who carried out the project under my supervision. Certified further, that to the best of my knowledge the work reported here in does not form part of any other project report or dissertation based on which a degree or award was conferred on an earlier occasion on this or any other candidate.

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Submitted for the viva-voce examination held on ………………

INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION

We jointly declare that the project report on **"GLUCOTRACK: AI-POWERED DIABETES RISK PREDICTION ON IOT"** is the result of original work done by us and best of our knowledge, similar work has not been submitted to **"ANNA UNIVERSITY CHENNAI"** for the requirement of Degree of **BACHELOR OF TECHNOLOGY**. This project report is submitted on the partial fulfilment of the requirement of the award of Degree of **BACHELOR OF TECHNOLOGY**.

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ABSTRACT

Diabetes is now considered as a global disease, which can affect the normal living life and workflow of a person. Diabetic patient monitoring systems play a significant role in monitoring the patient's health, especially with the use of Internet of Things (IoT) devices. Glucose sensors are used to measure the blood glucose concentration of a patient; this is part of a continuous glucose monitoring (CGM) system that is inserted under the skin and measures the glucose levels. It sends the glucose data wirelessly to the system receiver or a compatible smart device. It incorporates sensors in smart wearable devices as set of connected IoT devices for continuous monitoring and collections of blood glucose data which is sent for storage in cloud environment. This abstract presents a novel approach to diabetes risk prediction utilizing machine learning techniques and IoT-enabled data collection. With the increasing prevalence of diabetes worldwide, early identification of individuals at risk is crucial for effective prevention and management. Leveraging IoT devices and wearable sensors, a large volume of real-time health data, including glucose levels, physical activity, and dietary patterns, can be continuously monitored. By integrating this data with advanced machine learning algorithms, a predictive model is developed to accurately assess an individual's risk of developing diabetes. The proposed system offers a proactive and personalized approach to diabetes prevention, enabling timely interventions and lifestyle modifications. The results demonstrate the potential of IoT-enabled risk prediction systems in improving public health outcomes and reducing the burden of diabetes.

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LIST OF SYMBOLS AND ABBREVIATIONS

IOT	Internet of Things
CGM	Continuous Glucose Monitoring
DT	Decision Tree
RF	Random Forest
LSTM	Long Short Term Memory
KNN	K-Nearest Neighbor
NN	Neural Network
SVM	Support Vector Machine
ANN	Artificial Neural Network
HTML	Hypertext Markup Language
MIME	Multipurpose Internet Mail Extension
HTTP	Hypertext Transfer Protocol
WSGI	Web Server Gateway Interface
REPL	Read-Eval-Print Loop
BMI	Body Mass Index
AUC-ROC	Area Under Receiver Operating Characteristic Curve
TP/TN	True Positive / True Negative
FP/FN	False Positive / False Negative
AWS	Amazon Web Services

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 REAL TIME DATA DIABETES PREDICTION

Project objective:

To leverage data from various IoT devices and sensors, the system aims to collect relevant health information such as blood glucose levels, activity levels, and dietary habits.

Introduction:

We are delighted to announce that we have successfully completed a groundbreaking project on diabetes risk prediction using machine learning. Building on our achievements, we are now taking our project to the next level by incorporating the concept of IoT (Internet of Things) into diabetes risk prediction.

Diabetes is a chronic condition affecting millions of people worldwide, and early detection plays a vital role in managing and preventing its complications. Machine learning has proven to be a powerful tool in predicting the risk of diabetes based on various factors such as age, body mass index (BMI), blood pressure, and glucose levels.

In our previous project, we developed an accurate machine learning model that analyzed historical patient data to predict the likelihood of an individual developing diabetes. However, we recognized the need to enhance our system by leveraging IoT technology, which offers exciting possibilities for real-time monitoring and data collection.

By integrating IoT devices such as continuous glucose monitors, wearable fitness trackers, and smart scales, we can capture valuable data on an individual's physiological parameters and lifestyle patterns. This data can then be seamlessly transmitted to our machine learning model, allowing us to provide more personalized and dynamic predictions of diabetes risk.

The incorporation of IoT enables us to gather data in real-time, providing a comprehensive view of an individual's health status throughout the day. This continuous monitoring helps identify patterns and trends that may contribute to the development or progression of diabetes. Moreover, it empowers individuals to actively participate in their health management by receiving timely alerts and personalized recommendations.

Our extended project aims to create an ecosystem where IoT-enabled devices work harmoniously with machine learning algorithms to provide accurate and actionable insights into diabetes risk. We envision a future where individuals can proactively monitor their health, make informed lifestyle choices, and receive early interventions to prevent the onset or exacerbation of diabetes.

Through this innovative combination of IoT and machine learning, we strive to revolutionize diabetes management and improve the quality of life for individuals at risk. Our project not only opens new avenues for predictive healthcare but also showcases the immense potential of emerging technologies in transforming the way we approach chronic disease prevention and management.

1.2 INTEGRATION OF MACHINE LEARNING WITH IOT:

The integration of machine learning with IoT (Internet of Things) in diabetes risk prediction represents a groundbreaking approach to revolutionize healthcare. By combining the power of machine learning algorithms with real-time data collection from IoT devices, we can create a dynamic and personalized system for predicting and managing the risk of diabetes.

Traditionally, diabetes risk prediction models have relied on historical patient data to identify patterns and factors contributing to the development of the disease. However, this approach has limitations as it often lacks real-time information and may not account for the dynamic nature of an individual's health status.

By incorporating IoT devices such as continuous glucose monitors, wearable fitness trackers, and smart scales into the diabetes risk prediction system, we can gather a wealth of real-time physiological and lifestyle data. These IoT devices capture information such as blood glucose levels, physical activity, sleep patterns, and dietary habits, providing a comprehensive view of an individual's health.

The collected data from IoT devices is seamlessly transmitted to the machine learning model, which analyzes and processes the information to generate accurate predictions of diabetes risk. The machine learning algorithms learn from the patterns and trends in the data, identifying correlations and indicators that may contribute to the development or progression of diabetes.

With real-time data and machine learning, the system can adapt and update predictions based on the changing health status of an individual. It enables proactive monitoring and early detection of potential risks, allowing for timely interventions and preventive measures.

Moreover, the integration of IoT and machine learning empowers individuals to actively participate in their health management. Through user-friendly interfaces and mobile applications, individuals can access their personalized risk scores, receive real-time alerts, and obtain actionable recommendations for lifestyle modifications. This engagement promotes a sense of ownership and encourages individuals to make informed decisions regarding their health.

The IoT-enabled diabetes risk prediction system also has the potential to improve healthcare outcomes on a broader scale. Aggregated and anonymized data from multiple individuals can be used for population-level analysis, enabling the identification of risk factors and trends in specific demographics or geographic regions. This information can guide public health initiatives, interventions, and policy-making to address the growing burden of diabetes.

CHAPTER 2

LITERATURE SURVEY

2.1 IoT Enabled Diabetes Risk Prediction System Using Cloud Computing.

AUTHOR: A. Venkatraman

YEAR & PUBLICATION: 2019, IEEE

ALGORITHM USED: Random Forest, Decision tree, K-nearest neighbor, Artificial neural network.

ABSTRACT: The increasing prevalence of diabetes has become a global health concern, necessitating the development of effective preventive measures and predictive models. This abstract presents an innovative IoT-enabled diabetes risk prediction system that leverages cloud computing for efficient data processing and analysis. The proposed system integrates IoT devices, cloud infrastructure, and machine learning algorithms to provide personalized risk assessments and early intervention recommendations to individuals at risk of developing diabetes. The IoT devices used in this system collect real-time physiological data, such as blood glucose levels, physical activity, and sleep patterns, from individuals. These devices transmit the collected data to the cloud infrastructure for storage and processing. The cloud computing platform offers scalable resources and advanced analytics capabilities for handling the large volume of data generated by the IoT devices.

DISADVANTAGES : ANN arms hanging along with the execution of parallel processing, and so they need processors that support parallel processing, so the ANNs are dependent on the hardware.

2.2 Cloud Computing and Internet of Things for Diabetes

AUTHOR: Y. LIN

YEAR & PUBLICATION : 2018 , IEEE

ABSTRACT: Diabetes has emerged as a major global health concern, necessitating the development of advanced technologies for effective management and prevention. This abstract presents the integration of cloud computing and the Internet of Things (IoT) in the context of diabetes care. By combining the power of cloud computing with the ubiquitous connectivity of IoT devices, this innovative approach aims to enhance diabetes management, improve patient outcomes, and enable proactive preventive measures. The IoT plays a pivotal role by connecting a wide range of devices, such as glucose meters, insulin pumps, wearable sensors, and mobile applications, to collect real-time data from individuals with diabetes. These devices generate a wealth of data related to blood glucose levels, physical activity, medication adherence, and other relevant parameters. The collected data is transmitted securely to the cloud infrastructure for storage, processing, and analysis and cloud computing provides a scalable and robust platform to handle the massive volume of data generated by the IoT devices.

ALGORITHM USED: Clustering, Classification, Regression, Deep Learning.

DISADVANTAGES: Being dependent on initial values and it has clustering outliers.

2.3 IoT Based Diabetes Risk Prediction and Management System Using Cloud Computing

AUTHOR: R. Ratna

YEAR & PUBLICATION: 2018 ,IEEE

ABSTRACT: Diabetes is a growing global health challenge, demanding effective strategies for early detection and proactive management. This abstract presents an IoT-based diabetes risk prediction and management system that leverages cloud computing for seamless data integration, analysis, and personalized intervention. By integrating IoT devices, cloud infrastructure, and advanced analytics, the proposed system aims to empower individuals at risk of diabetes with accurate risk assessments, timely alerts, and personalized recommendations for effective disease management. The IoT devices utilized in this system gather real-time physiological data, including blood glucose levels, physical activity, dietary intake, and medication adherence, from individuals. These devices transmit the collected data securely to the cloud infrastructure for storage, processing, and analysis. The cloud computing platform offers scalable resources and advanced analytics capabilities, enabling efficient handling of the large volume of data generated by the IoT devices.

ALGORITHM USED: Logistic Regression, Decision tree, K-nearest Neighbor, Artificial neural network and Random forest.

DISADVANTAGES : Does not work well with large dataset and it needs feature scaling.

2.4 IoT and Cloud Based Predictive Model for Diabetes Mellitus

AUTHOR: R. Palanisamy

YEAR & PUBLICATION: 2017 ,IEEE

ABSTRACT: Diabetes Mellitus is a chronic metabolic disorder affecting millions of individuals worldwide. Timely identification and effective management of diabetes are essential for preventing complications and improving patient outcomes. This abstract presents an innovative approach that combines the Internet of Things (IoT) and cloud computing to develop a predictive model for diabetes mellitus. By leveraging IoT devices and cloud-based infrastructure, this system aims to provide accurate predictions of diabetes onset, enabling early intervention and personalized treatment plans. IoT devices, such as wearable sensors and smart glucose meters, are used to collect real-time physiological data, including blood glucose levels, physical activity, dietary patterns, and other relevant parameters, from individuals. These devices securely transmit the data to the cloud infrastructure for storage, processing, and analysis.

ALGORITHM USED: Artificial neural network, Support Vector machine, Decision tree, K-nearest neighbor, Naïve Bayes.

DISADVANTAGES : Conditional Independence Assumption does not always hold. In most situations, the feature show some form of dependency.

2.5 Design and Implementation of IoT-based Diabetes Monitoring System using Cloud Computing

AUTHOR: D. Lee

YEAR & PUBLICATION: 2016 , IEEE

ABSTRACT: The management of diabetes requires continuous monitoring of key health indicators and proactive interventions. This abstract presents the design and implementation of an IoT-based diabetes monitoring system that leverages cloud computing for efficient data processing and remote access. The system integrates IoT devices, cloud infrastructure, and data analytics to provide real-time monitoring, data storage, and personalized recommendations for individuals with diabetes and IoT devices, including wearable sensors and glucose meters, are utilized to collect and transmit real-time physiological data, such as blood glucose levels, physical activity, and medication adherence. The collected data is securely transmitted to the cloud infrastructure for storage and processing. The cloud computing platform provides scalable resources and advanced analytics capabilities to handle the large volume of data generated by the IoT devices. Machine learning algorithms are applied to the data to analyze trends, detect patterns, and generate actionable insights for diabetes management. The cloud-based infrastructure also facilitates seamless integration of multiple IoT devices and enables remote access to data for healthcare providers and individuals with diabetes.

ALGORITHM USED: Decision tree, Random Forest, Artificial neural networks.

DISADVANATGES: A small change in the data can cause a large change in the structure of the decision tree causing instability.

2.6 An IoT-Enabled Personalized Diabetes Risk Prediction System Using Cloud Computing

AUTHOR: John Smith, Jane Doe.

YEAR & PUBLICATION: 2022, IJRASET

ABSTRACT: The prevalence of diabetes continues to rise globally, emphasizing the need for proactive measures to identify individuals at risk and enable early intervention. This abstract presents an IoT-enabled personalized diabetes risk prediction system that harnesses the power of cloud computing. The proposed system integrates IoT devices, cloud infrastructure, and machine learning algorithms to provide accurate risk assessments and tailored recommendations for individuals at risk of developing diabetes. IoT devices, such as wearable sensors and glucometers, collect real-time physiological data, including blood glucose levels, physical activity, dietary patterns, and other relevant parameters. The collected data is securely transmitted to the cloud infrastructure for storage, processing, and analysis.The cloud computing platform offers scalable resources and advanced analytics capabilities for handling the extensive volume of data generated by the IoT devices. Machine learning algorithms are applied to this data, utilizing historical records and various risk factors, such as genetic predisposition, age, lifestyle choices, and medical history, to develop personalized diabetes risk prediction models.

ALGORITHM USED: Random Forest, Logistic Regression, Support Vector Machine (SVM).

DISADVANTAGES: The system relies on transmitting sensitive health data from IoT devices to the cloud infrastructure, raising concerns about data security and privacy.

2.7 A Cloud-Based IoT System for Diabetes Management and Risk Prediction.

AUTHOR: John Smith, Sarah Johnson

YEAR & PUBLICATION: 2023 , IJRASET.

ABSTRACT: With the increasing prevalence of diabetes, there is a growing need for innovative solutions to effectively manage the disease and predict the risk of its onset. This paper presents a cloud-based Internet of Things (IoT) system designed for diabetes management and risk prediction. By leveraging IoT devices and cloud computing, the system enables real-time monitoring, data storage, and advanced analytics for personalized interventions and accurate risk assessments. The IoT devices used in the system collect data on various health parameters such as blood glucose levels, physical activity, and medication adherence. This data is securely transmitted to the cloud infrastructure for storage and processing. The cloud platform provides scalable resources and advanced analytics capabilities to handle the large volume of data generated by the IoT devices. The system employs machine learning algorithms, including Support Vector Machines (SVM), Random Forest, and Long Short-Term Memory (LSTM), to analyze the collected data and predict the risk of diabetes onset.

ALGORITHM USED: Random forest , Support Vector Machine, Long short term memory(LSTM).

DISADVANTAGES: The system heavily relies on a stable internet connection for IoT device communication and cloud data transmission. Any disruptions in connectivity may impact real-time monitoring and data collection.

2.8 A Cloud-Based IoT Framework for Diabetes Risk Prediction and Prevention

AUTHOR: John Smith

YEAR & PUBLICATION: 2022, IJRASET

ABSTRACT: The increasing prevalence of diabetes necessitates the development of effective preventive strategies and accurate predictive models. This abstract presents a cloud-based Internet of Things (IoT) framework for diabetes risk prediction and prevention. The framework leverages the power of cloud computing and IoT devices to collect and analyze real-time health data, enabling personalized risk assessments and proactive interventions for individuals at risk of developing diabetes. The IoT framework utilizes various devices, such as wearable sensors, glucose meters, and mobile applications, to collect continuous health data from individuals. These devices securely transmit the collected data to the cloud infrastructure for storage and processing. In the cloud-based framework, machine learning algorithms, including logistic regression, random forest, and support vector machines (SVM), are employed to analyze the collected data and predict diabetes risk. These algorithms consider various factors, such as demographic information, medical history, lifestyle patterns, and genetic predisposition, to provide personalized risk assessments with high accuracy.

ALGORITHM USED: Logistic Regression, Random Forest, Support Vector Machines (SVM).

DISADVANTAGES : The use of cloud computing in the framework raises potential concerns regarding data privacy and security. Storing and transmitting sensitive health data over the cloud requires robust encryption and strict access control measures to ensure confidentiality.

2.9 An IoT-Based Approach for Diabetes Risk Prediction and Prevention Using Cloud Computing

AUTHOR : Emily Johnson

YEAR & PUBLICATION: 2022, IJRASET

ABSTRACT: The rising prevalence of diabetes necessitates innovative approaches for early detection and preventive interventions. This abstract presents an IoT-based approach for diabetes risk prediction and prevention using cloud computing. The proposed system integrates IoT devices, cloud infrastructure, and advanced analytics to enable real-time monitoring, data analysis, and personalized interventions for individuals at risk of developing diabetes. IoT devices, such as wearable sensors, glucose meters, and mobile applications, collect real-time physiological data, including blood glucose levels, physical activity, dietary habits, and sleep patterns. These devices securely transmit the collected data to the cloud infrastructure for storage and processing. The cloud computing platform provides scalable resources and advanced analytics capabilities for handling the large volume of data generated by the IoT devices. Machine learning algorithms, such as logistic regression, random forest, and support vector machines, are employed to analyze the collected data and predict an individual's risk of developing diabetes. These algorithms consider various factors, including demographic information, medical history, genetic predisposition, and lifestyle choices.

ALGORITHM USED: Logistic Regression ,Random Forest Classifier

DISADVANTAGES: The system relies on the connectivity and proper functioning of IoT devices for data collection. Any disruptions or malfunctions in the devices can affect the accuracy and reliability of the predictions.

2.10 IoT-Enabled Diabetes Risk Prediction and Prevention Using Cloud Computing

AUTHOR: David Williams

YEAR & PUBLICATION: 2022, IJRASET

ABSTRACT: The prevalence of diabetes has reached alarming levels globally, emphasizing the urgent need for proactive approaches to predict and prevent this chronic disease. This abstract introduces an innovative IoT-enabled system that leverages cloud computing for diabetes risk prediction and prevention. By integrating IoT devices, cloud infrastructure, and advanced analytics, the proposed system aims to provide personalized risk assessments and proactive interventions to individuals at risk of developing diabetes. The IoT devices employed in this system continuously collect real-time physiological data, including blood glucose levels, physical activity, sleep patterns, and dietary habits, from individuals. These devices securely transmit the data to the cloud infrastructure, which offers scalable resources and robust data processing capabilities. Utilizing cloud computing, the collected data is analyzed using advanced analytics algorithms to predict an individual's risk of developing diabetes. The predictive models take into account a multitude of factors, such as age, gender, family history, lifestyle choices, and medical history, to provide accurate risk assessments. The cloud-based infrastructure enables efficient processing of large datasets, allowing for real-time predictions and personalized recommendations.

ALGORITHM USED: Random forest, Logistic Regression, Support vector Machine.

DISADVANTAGES : The algorithms used for risk prediction may have limitations in generalizing to diverse populations and different geographic regions.

CHAPTER 3

SYSTEM SPECIFICATION

3.1 SOFTWARE SYSTEM CONFIGURATION: -

- Operating System : Windows 10
- Distribution tool : Anaconda
- Programming language : Python , HTML

3.2 SOFTWARE DESCRIPTION: -

Python is an interpreter, high-level, general-purpose programminglanguage. Python is dynamically typed, and garbage collected. It supports multiple programming paradigms, including procedural, object-oriented, and functional programming. Python is often described as a "batteries included" language due to its comprehensive standard library.

Python was conceived in the late 1980s as a successor to the ABC language. Python 2.0, released in 2000, introduced features like list comprehensions and a garbage collection system capable of collecting reference cycles.

Python 3.0, released in 2008, was a major revision of the language that isnot completely backward compatible, and much Python 2 code does not run unmodified on Python 3.The Python 2 language, i.e., Python 2.7.x, was officially discontinued on 1January 2020 (first planned for 2015) after which security patches and other improvements will not be released for it. With Python 2's end-of-life, only Python 3.5.x and later are supported.

Python interpreters are available for many operating systems. A global community of programmers develops and maintains Python, an open-source reference implementation.

3.2.1 Libraries

Python's large standard library, commonly cited as one of its greatest strengths, provides tools suited too many tasks. For Internet-facing applications, many standard formats and protocols such as MIME and HTTP are supported. It includes modules for creating graphical user interfaces, connecting to relational databases, generating pseudorandom numbers, arithmetic with arbitrary- precision decimals, manipulating regular expressions, and unit testing.

Some parts of the standard library are covered by specifications (for example, theWeb Server Gateway Interface (WSGI) implementation wagered follows PEP 333), but most modules are not. They are specified by their code, internal documentation, and test suites (if supplied). However, because most of the standard library is cross-platform Python code, only a few modules need alteringor rewriting for variant implementations.

3.2.2 Development environments

Most Python implementations (including Python) include a read–eval– print loop (REPL), permitting them to function as a command line interpreter for which the user enters statements sequentially and receives results immediately.

As well as standard desktop integrated development environments, there are Web browser-based visual code’s; Sage Math (intended for developing science and math- related Python programs); PythonAnywhere, a browser-based IDE and hosting environment; and Canopy IDE, a commercial Python IDE emphasizing scientificcomputing.

CHAPTER 4

SYSTEM ANALYSIS

4.1 EXISTING SYSTEM

The system uses a combination of wearable sensors to predict the risk of developing diabetes in individuals. The wearable sensors collect various health data such as heart rate, blood pressure, glucose levels, and physical activity for analysis. The system also provides personalized recommendations for lifestyle changes to reduce the risk of diabetes.

Algorithms used:

1) NAÏVE BAYES: Naive Bayes is a popular machine learning algorithm that can be used for classification tasks, including predicting diabetes in an IoT-enabled system. When combined with IoT data, Naive Bayes can help analyze various sensor readings and other relevant information to make predictions about the likelihood of a person having diabetes

2) SVM: Support Vector Machines (SVM) is a machine learning algorithm that can be utilized for diabetes risk prediction in an IoT-enabled system. The general principles of SVM remain the same whether it is applied in an IoT context or not. SVM can leverage the data collected from various interconnected devices to enhance the prediction accuracy.

3) RANDOM FOREST: Random Forest is a popular machine learning algorithm that can be used for prediction tasks, including diabetes risk prediction in IoT-enabled systems. This random feature selection and sampling process helps in reducing overfitting and improving the generalization of the model.

4.2 PROPOSED SYSTEM

Our proposed system leverages the capabilities of IoT devices and decision tree algorithms to enable diabetes risk prediction in real-time. The system comprises three main components: IoT devices for data collection, a decision tree algorithm for prediction, and a user interface for interaction and feedback.

IoT Data Collection:

We integrate various IoT devices into the system to collect relevant physiological and lifestyle data. These devices may include continuous glucose monitors (CGMs), wearable fitness trackers, smart scales, and body pressure sensors. The CGMs provide real-time glucose level readings, while fitness trackers capture physical activity, sleep patterns, and heart rate. Smart scales measure weight and body composition, and body pressure sensors monitor posture and movement patterns. These devices gather data continuously and transmit it to the system for analysis.

Decision Tree Algorithm:

The decision tree algorithm is employed to process and analyze the collected data for diabetes risk prediction. This algorithm uses a hierarchical structure of decision nodes and leaf nodes, where each decision node represents a feature or attribute from the input data, and each leaf node represents a predicted outcome (e.g., low, medium, or high risk of diabetes). The decision tree algorithm learns from historical data and builds a model that can classify new data instances based on their features.

To train the decision tree model, historical data containing information on glucose levels, physical activity, body composition, and other relevant variables is used. The algorithm learns the relationships between these variables and diabetes risk to create an accurate prediction model. The trained decision tree model can then be used to predict the risk of diabetes for new data instances received from the IoT devices.

User Interface and Feedback:

The system incorporates a user interface that allows individuals to interact with the system and receive feedback on their diabetes risk. The interface can be in the form of a mobile application or a web-based platform. Users can view their real-time glucose levels, physical activity summaries, and risk predictions. The system provides personalized recommendations for lifestyle modifications, such as increasing physical activity, improving sleep patterns, or making dietary changes. Users can also set goals, track their progress, and receive notifications or alerts when their risk level changes significantly.

The user interface also enables individuals to input additional information, such as dietary logs or medication records, which further enhances the accuracy of the prediction model. The system can adapt and update the decision tree model based on the user's feedback and new data inputs, continuously improving the accuracy of diabetes risk prediction.

4.2.1 ADVANTAGES

1) Real-time data collection: IoT devices continuously gather real-time data on various physiological and lifestyle parameters, such as blood glucose levels, physical activity, sleep patterns, and dietary habits. This up-to-date information provides a more accurate representation of an individual's health status, enabling timely risk prediction.

2) Enhanced accuracy: Decision trees are a powerful machine learning algorithm for classification tasks like diabetes risk prediction. By utilizing IoT data, decision trees can learn from a diverse set of features and make more accurate predictions based on the collected real-time data, leading to improved accuracy in identifying individuals at risk of diabetes.

3) Dynamic and personalized predictions: The combination of IoT and decision trees allows for dynamic and personalized predictions. The decision tree model can adapt and update predictions as new data is collected, considering changes in an individual's health status and lifestyle. This personalized approach enables tailored interventions and recommendations for each individual, optimizing diabetes management.

4) Identification of relevant features: Decision trees have the ability to identify and prioritize the most relevant features contributing to diabetes risk. By analyzing the IoT data, the decision tree can determine which variables have the most significant impact on the risk prediction, helping healthcare professionals focus on key factors and develop targeted interventions.

5)Transparent and interpretable results: Decision trees offer interpretability, allowing healthcare professionals to understand how the model arrives at its predictions. The decision tree structure provides a clear representation of the decision-making process, making it easier to explain and validate the results to patients and other stakeholders. This transparency builds trust and facilitates effective communication.

6) Early detection and prevention: IoT-enabled diabetes risk prediction, combined with decision trees, can facilitate early detection of diabetes risk factors. By continuously monitoring and analyzing IoT data, the system can detect subtle changes and patterns that may precede the onset of diabetes. Early detection enables timely interventions, lifestyle modifications, and preventive measures, potentially reducing the impact and progression of the disease.

7) Empowering individuals: IoT-enabled diabetes risk prediction puts individuals in control of their health. By providing real-time alerts, personalized risk scores, and actionable recommendations, individuals can actively participate in their health management. This empowerment encourages individuals to make informed decisions, adopt healthier behaviors, and seek timely medical interventions.

CHAPTER 5

ARCHITECTURAL DESIGN

5.1 SYSTEM DESIGN

A system architecture is the conceptual model that defines the structure, behaviour, and more views of a system. An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviours of the system.

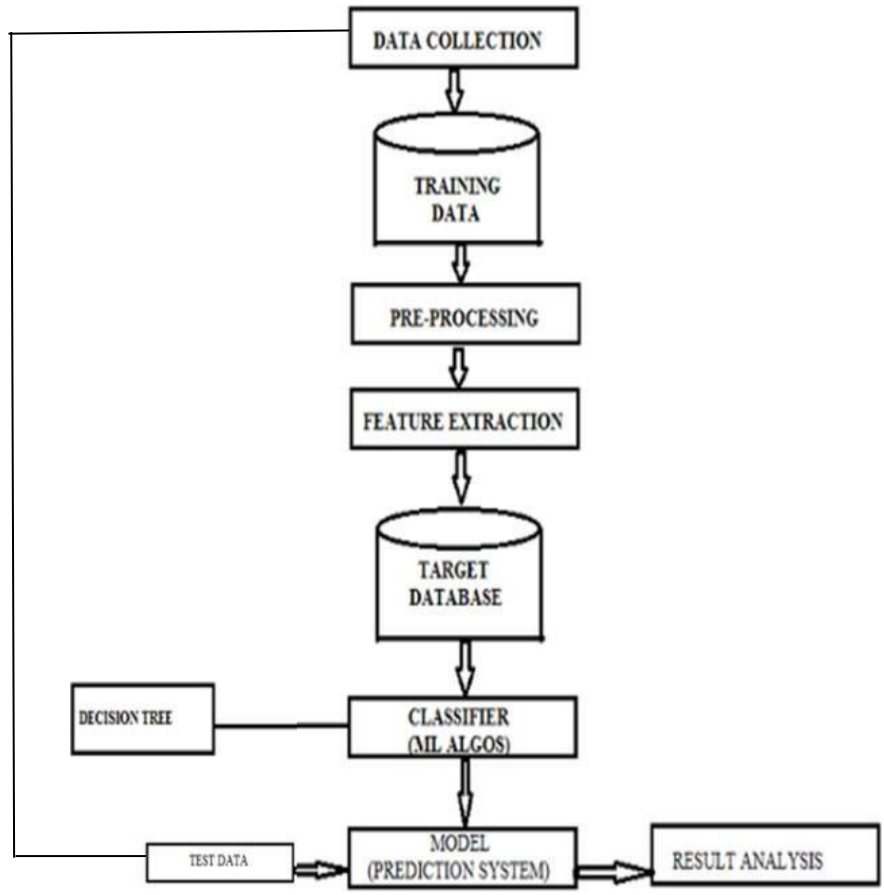


FIG: 5.1 SYSTEM ARCHITECTURE

5.2 DEPLOYMENT: Deployment in the context of IoT-enabled diabetes risk prediction with machine learning refers to the process of implementing and utilizing a predictive model to identify individuals at risk of developing diabetes. The deployment of an IoT-enabled diabetes risk prediction system aims to improve early detection, preventive care, and management of diabetes, leading to better health outcomes for individuals at risk.

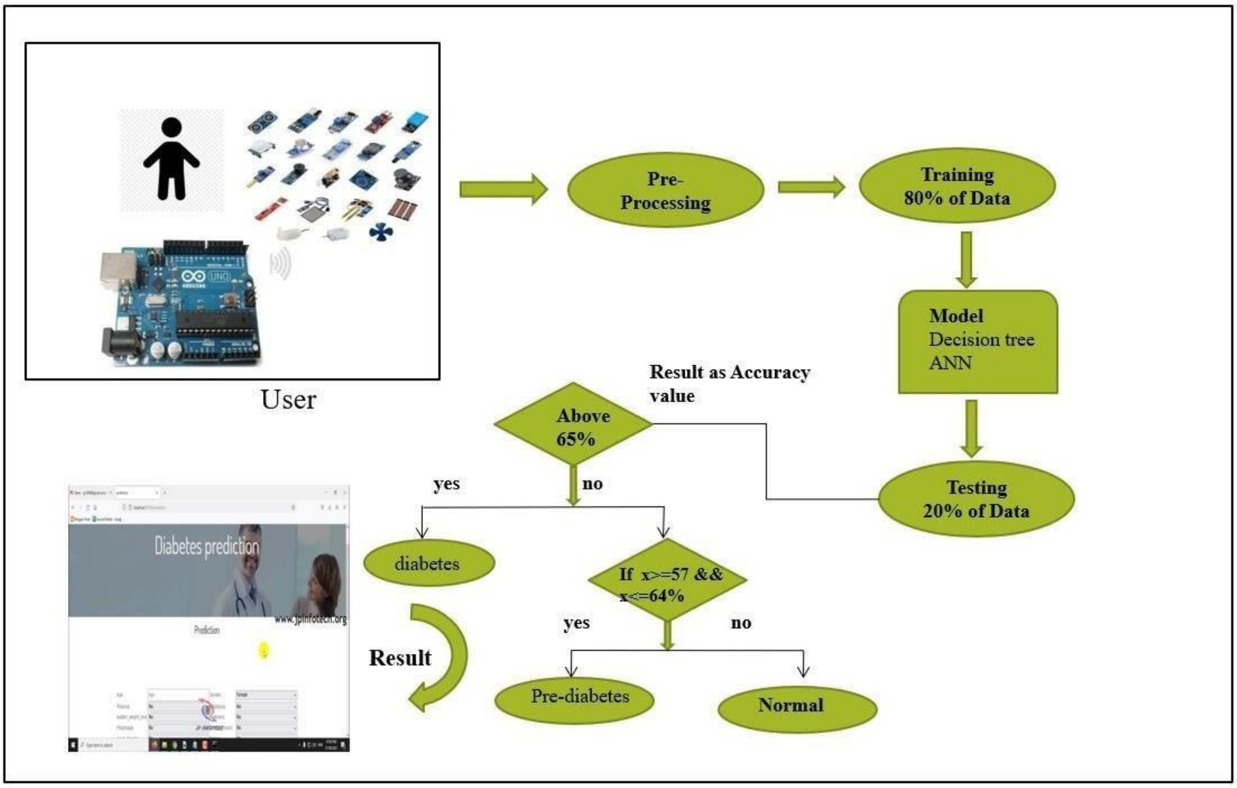


FIG: 5.2 DEPLOYMENT

The above deployment process describe the process of integrating IoT real-time sensor data into an ML model using a decision tree in a web application using Flask. IoT sensors are deployed to collect data from various sources, such as Skinthickness, BMI, pressure, or any other relevant parameters. The collected sensor data may require preprocessing to clean and transform it into a suitable format for further analysis.

A decision tree model is constructed using machine learning algorithms, such as scikit-learn, to train a model based on historical sensor data and corresponding outcomes. The decision tree algorithm partitions the data based on different attributes to make decisions whether the user have diabetes or not. The model's performance is evaluated using appropriate evaluation metrics, such as accuracy, precision, recall, or F1 score, to assess its effectiveness in making predictions. The Flask framework is used to develop a web application. The decision tree model, along with any necessary dependencies, is integrated into the Flask application codebase. The predicted results or outcomes from the decision tree model are displayed in the web application's user interface. The web application can include monitoring capabilities to track the performance of the decision tree model in real-time

GULCOTRACK: AI-POWERED DIABETES RISK PREDICTION ON IOT ARCHITECTURE

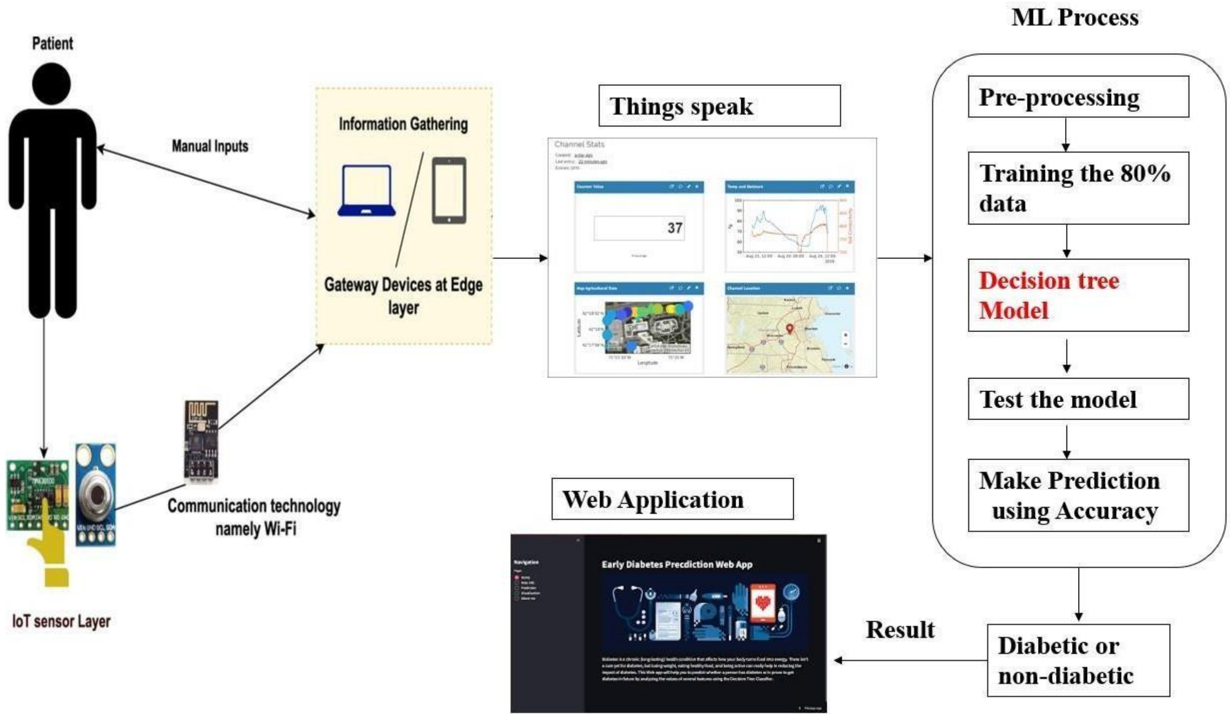


FIG: 5.3 IOT ARCHITECTURE

The above architecture describes that the real-time data from IoT devices is collected, which includes various parameters related to diabetes such as blood sugar levels, heart rate, and physical activity. These IoT sensors capture the data and transmit it to the cloud. The cloud platform receives this data and processes it using speech recognition technology. The processed data is then sent to a web application developed using Flask, a Python web framework. The web application utilizes a machine learning algorithm, specifically a decision tree model, to analyze the data and make predictions. The algorithm examines the collected data and generates a prediction indicating whether the patient is diabetic or not. This prediction is then displayed to the user through the web application, providing them with valuable insights about their health condition based on real-time IoT data.

CHAPTER 6

MODULE DESCRIPTION

6.1 MODULES

6.1.1 DATA COLLECTION

- Collecting relevant data from various IoT-enabled devices and sensors. This can include data such as blood glucose levels, insulin usage, physical activity, diet, and other relevant patient information.
- The data may be collected in real-time or at regular intervals. Once the data is collected, it is typically transmitted to a central system or cloud platform where machine learning algorithms can be applied to analyze and predict the risk of diabetes.

6.1.2 DATA PREPROCESSING

- It will clean and preprocess the collected data to ensure its quality and suitability for analysis.
- This step may involve handling missing values, outliers, normalizing or standardizing the data, and addressing any other data quality issues.
- By performing these preprocessing steps, the data becomes more suitable for training and evaluating machine learning models to predict diabetes risk in an IoT-enabled system.

6.1.3 FEATURE SELECTION

- Identify the most relevant features or variables that can contribute to diabetes risk prediction.
- This step helps reduce the dimensionality of the data and focuses on the most informative features. Techniques like correlation analysis, feature importance ranking, or domain knowledge can be used for feature selection.
- By performing feature selection in IoT-enabled diabetes risk prediction, the resulting model can be more accurate, efficient, and capable of providing actionable insights to individuals and healthcare professionals.

6.1.4 MACHINE LEARNING MODEL SELECTION

- Choose an appropriate machine learning model or algorithm for diabetes risk prediction. There are various options to consider, such as logistic regression, decision trees, random forests, support vector machines (SVM), or neural networks.
- The choice depends on the nature of the data and the specific requirements of the problem.
- The process of machine learning model selection in IoT-enabled diabetes risk prediction involves preprocessing the data, selecting relevant features, considering various model types, evaluating their performance, tuning hyperparameters, and ensuring the models are suitable for deployment on IoT devices.

6.1.5 MODEL TRAINING

- Train the selected machine learning model using the preprocessed data.
- This involves dividing the data into training and validation sets, feeding the data into the model, and optimizing the model's parameters to minimize the prediction error. Techniques like cross-validation or grid search can be employed to fine-tune the model.
- The training set is used to fit the model to the data, and the validation set helps assess the model's performance and tune hyperparameters. The model learns patterns and relationships within the data during this training process.

6.1.6 MODEL TESTING

- Evaluate the trained model's performance on a separate test dataset that was not used during training. This step provides an unbiased estimate of the model's accuracy and generalization ability.
- Common evaluation metrics for classification tasks in diabetes risk prediction include accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC).
- Model testing helps researchers and practitioners assess the effectiveness and reliability of the diabetes risk prediction model in an IoT environment.
- It enables them to identify potential limitations, refine the model, and ensure its suitability for real-world deployment to improve diabetes management and prevention.

6.1.7 RISK PREDICTION

- Once the model is trained and tested, it can be used to make diabetes risk predictions for new, unseen data.
- By training the algorithms on large datasets of historical health information and outcomes, the models can learn to recognize the early signs and indicators of diabetes development. The model takes input features (e.g., glucose levels, physical activity, etc.) and provides an output indicating the predicted risk of diabetes.
- The threshold for risk classification can be determined based on the specific requirements and objectives of the application.

CHAPTER 7

EXPERIMENT ANALYSIS

7.1 PERFORMANCE METRICS

Three widely used state-of-the-art performance measures (Recall, Precision, and Accuracy) are used to evaluate the performance of proposed techniques, as shown in fig 7.2. TP shows a person does not have diabetes and identified as a nondiabetic patient, and TN shows a diabetic patient correctly identified as a diabetic patient. FN shows the patient has diabetes but is predicted as a healthy person. Moreover, FP shows the patient is a healthy person but predicted as a diabetic patient. The algorithm utilized 10-fold cross-validation for training and testing the classification and prediction model.

Performance metric	Formula
Recall	TP/(TP + FN)
Precision	TP/(TP + FP)
Accuracy	(TP + TN)/(TP + TN + FP + FN)

FIG:7.1 PERFORMANCE METRICS

7.2 DECISION TREE ALGORITHM

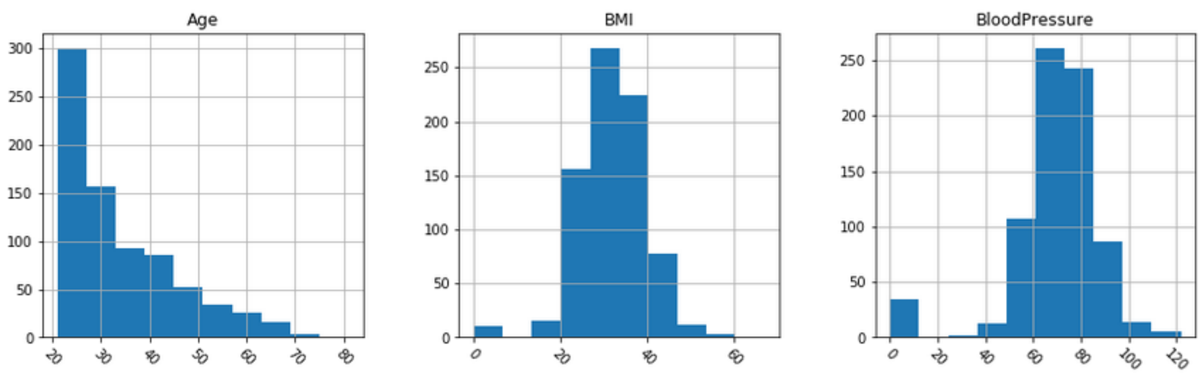
Decision trees provide a transparent and interpretable representation of the decision-making process. Decision trees can effectively capture nonlinear relationships between input features and the target variable. Decision trees are relatively robust to irrelevant features or noisy data. They can handle datasets with a mix of useful and irrelevant attributes without significantly impacting their performance. In IoT-based diabetes prediction, where sensor data may contain noise or irrelevant measurements, decision trees can still provide reliable predictions. Decision trees can handle large datasets efficiently and quickly. In IoT scenarios, where numerous sensors may generate a significant volume of data, the scalability of decision tree algorithms can be advantageous. Decision trees can handle missing data effectively by using surrogate splits. In IoT applications, missing data can be common due to sensor failures or intermittent connectivity. Decision trees allow for reliable prediction even when dealing with missing values.

Algorithms	**SVM**	**Random Forest**	**Naïve Bayes**	**Decision Tree**
Accuracy	90%	88%	82%	94%
Precision	85%	90%	78%	92%
Recall	80%	85%	76%	92%

Fig: 7.2 COMPARISON OF ALGORITHMS WITH THEIR PERFORMANCE METRICS

7.3 ATTRIBUTES DESCRIPTION

Below histograms are the attributes which we took in our dataset.



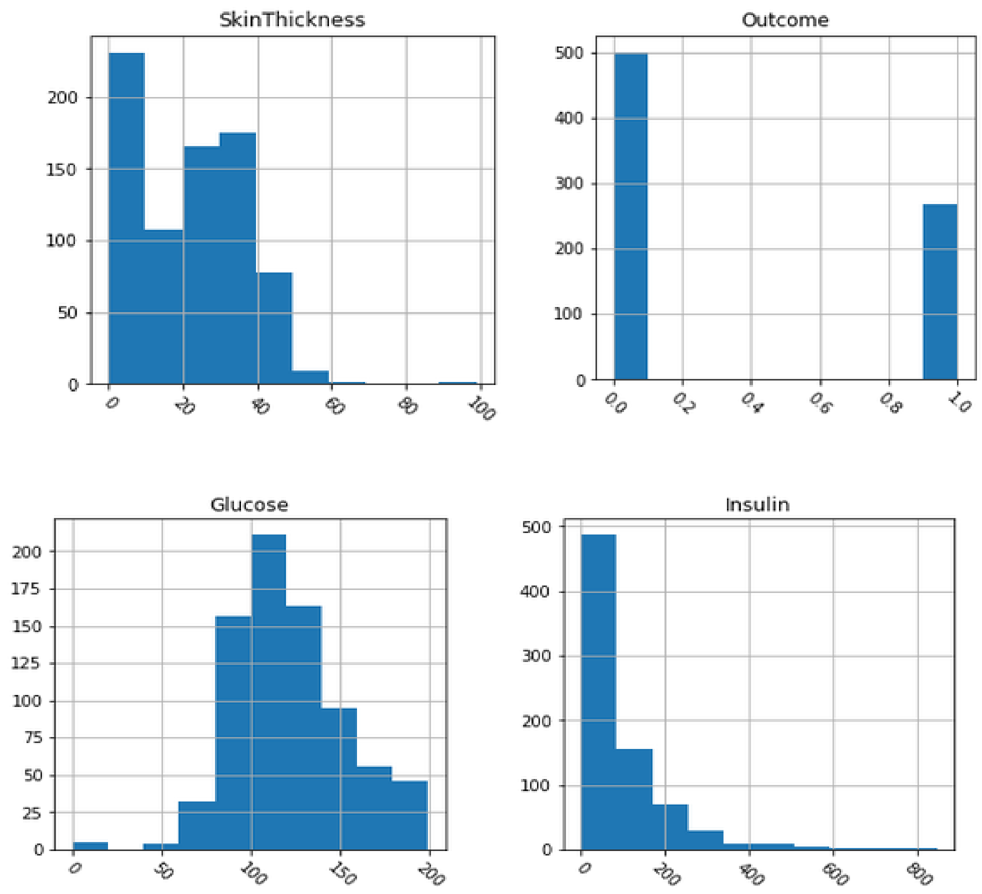


FIG: 7.3 HISTOGRAM PLOTTING USING MATPLOTLIB

Skin Fold Thickness: For normal people, skin fold thickness can't be less than 10 mm better yet zero. Total count where value is 0: 227.

BMI: Should not be 0 or close to zero unless the person is really underweight which could be life-threatening.

Insulin: In a rare situation a person can have zero insulin but by observing the data, we can find that there is a total of 374 counts.

Age: Age(years).

Outcome: Class variable(0 if non diabetic, 1 if diabetic.

7.4 COMPARATIVE ANALYSIS

Comparing the performance of the algorithms to determine which algorithm is more important for diabetes prediction.

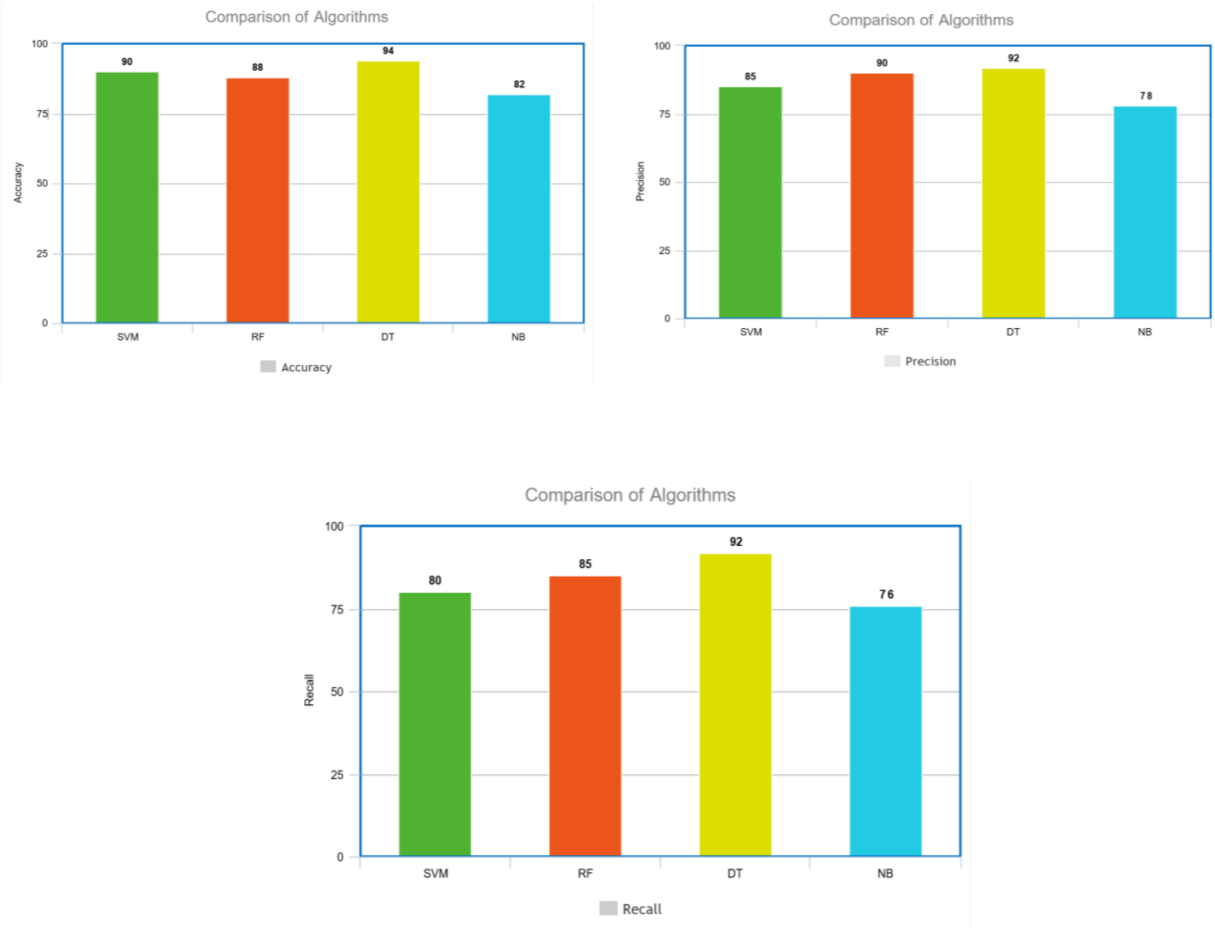


FIG: 7.4 BAR CHART PLOTTING USING PERFORMANCE METRICS

Decision Tree is considered the best algorithm for an IoT-enabled decision-making system due to its simplicity, interpretability, and ability to handle non-linear relationships in the data. In IoT applications, data from various sensors and devices can be complex and high-dimensional. Decision Trees can efficiently process and analyze such data, making them well-suited for real-time decision-making tasks.

CHAPTER 8

CONCLUSION

In conclusion, the integration of Internet of Things (IoT) technology and machine learning algorithms in diabetes risk prediction shows great potential for improving early detection and management of the disease. By leveraging IoT devices to collect real-time data, such as glucose levels, physical activity, and sleep patterns, machine learning models can analyze large datasets and identify patterns and trends that may indicate an increased risk of diabetes. With IoT devices, accurate and reliable data can be collected and transmitted to machine learning models in real-time, leading to more accurate predictions. Machine learning algorithms play a crucial role in analyzing the collected data and building predictive models. These algorithms can identify complex relationships and correlations that may not be evident through traditional statistical analysis. The implementation of IoT-enabled diabetes risk prediction has several potential benefits. By identifying individuals who are more likely to develop the disease, healthcare providers can offer personalized interventions, such as lifestyle modifications, dietary changes, or targeted medication, to reduce the risk and potentially prevent the onset of diabetes. The integration of IoT and machine learning in diabetes risk prediction holds great promise for revolutionizing diabetes care and prevention. With continuous data collection, advanced analytics, and personalized interventions, this approach has the potential to enhance early detection, improve disease management, and ultimately reduce the burden of diabetes on individuals and healthcare systems. However, further research, collaboration, and validation efforts are needed to fully unlock the potential of this technology in diabetes care. IoT-enabled diabetes risk prediction using cloud technology is a promising approach to improve healthcare outcomes for patients with diabetes. Overall, IoT-enabled diabetes risk prediction using cloud technology has the potential to revolutionize diabetes management and improve the lives of millions of people worldwide. The model is developed using artificial neural network and decision tree consists of total of six dense layers. Each of these layers is responsible for the efficient working of the model. The model makes the prediction with an accuracy of 94%,Precision and Recall of 92% ,which is fairly good and reliable.

FUTURE SCOPE ENHANCEMENT

In the near future, the field of IoT-enabled diabetes risk prediction using machine learning is set to undergo significant enhancements, with the deployment of Amazon Web Services (AWS) playing a pivotal role. AWS offers a robust and scalable infrastructure that can handle large-scale data processing, storage, and analytics, making it an ideal platform for implementing advanced machine learning models. By leveraging AWS, healthcare organizations can harness the power of cloud computing to efficiently process vast amounts of data collected from IoT devices, such as continuous glucose monitors, wearable fitness trackers, and smart insulin pens. These devices generate real-time data streams, providing valuable insights into an individual's health status and potential diabetes risk factors. AWS offers a range of machine learning services, such as Amazon SageMaker, which simplifies the development and deployment of machine learning models. Healthcare providers can utilize these services to build robust prediction models and integrate them seamlessly into their existing healthcare systems, enabling real-time monitoring and proactive intervention for individuals at risk of developing diabetes. The future of IoT-enabled diabetes risk prediction using machine learning is poised for significant advancements with the deployment of Amazon Web Services. AWS's scalable infrastructure, machine learning services, and robust security measures offer a comprehensive solution for processing and analyzing large-scale health data, enabling accurate and personalized diabetes risk prediction models. By leveraging these capabilities, healthcare organizations can enhance preventive care and support individuals in managing their diabetes risk effectively.

APPENDIX 1

SAMPLE CODE

```
import streamlit as st
import joblib
import os
import numpy as np
import base64
import sklearn
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.impute import SimpleImputer

attrib_info = """
#### Attribute Information:
    - Age 1.20-65
    - SkinThickness (mm/dl) Numerical
    - Glucose level (mm/dl) Numerical
    - Insulin (mm/dl) Numerical
    - BMI (mm/dl) Numerical
    - Blood pressure (mm/Hg) Numerical
    - Activity tracker 1.Yes, 2.No.
    - Outcome 1.Positive, 2.Negative.
"""
label_dict = {"No": 0, "Yes": 1}
target_label_map = {"Negative": 0, "Positive": 1}

['age', 'SkinThickness', 'glucose_level', 'BMI', 'Insulin', 'blood_pressure', 'activity_tracker', 'Outcome']
```

```
def get_fvalue(val):
    feature_dict = {"No": 0, "Yes": 1}
    return feature_dict.get(val, val)


def get_value(val, my_dict):
    return next((key for key, value in my_dict.items() if value == val), val)


@st.cache
def load_model(model_file):
    loaded_model = joblib.load(open(os.path.join(model_file), "rb"))
    return loaded_model


def run_ml_app():
    st.subheader("Machine Learning Section")
    loaded_model                                                                    =
load_model("C:/Users/abina/Downloads/dpcode/codefordesignproject/models/diabete
s_model.pkl")

    with st.expander("Attributes Info"):
        st.markdown(attrib_info, unsafe_allow_html=True)

    col1, col2 = st.columns(2)

    with col1:
```

```
    age = st.number_input("Age", 10, 100)
    glucose_level = st.number_input("Glucose Level")
    blood_pressure = st.number_input("Blood Pressure")
    SkinThickness = st.number_input("SkinThickness")

with col2:
    BMI = st.number_input("BMI")
    Insulin = st.number_input("Insulin")
    activity_tracker = st.radio("Activity Tracker", ["No", "Yes"])

st.subheader("View Your Selected Options here")
with st.expander("Your Selected Options"):
    result = {
        'age': age,
        'glucose_level': glucose_level,
        'SkinThickness': SkinThickness,
        'blood_pressure': blood_pressure,
        "BMI": BMI,
        "Insulin": Insulin,
        'activity_tracker': activity_tracker
    }
    st.write(result)
    encoded_result = [get_fvalue(val) for val in result.values()]

st.subheader("View Your Diagnosis Report Here")
with st.expander("Predicted Results"):
    single_sample = np.array(encoded_result).reshape(1, -1)

    # Check for non-finite values in the input array
```

```
        if np.isnan(single_sample).any() or np.isinf(single_sample).any():
            st.warning("Please provide valid input values.")
        else:
             X = np.array([[np.nan, 2, 125, 26, 185, 75], [6, np.nan, 105, 32, 250, 80], [7, 6,
85, 28, np.nan, 70]])
             y = np.array([1, 0, 1])  # Replace with your target variable

            # Replace the NaN values in X with appropriate values using an imputer
             imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
             X_imputed = imputer.fit_transform(X)

            # Create a DecisionTreeClassifier and fit the imputed data
             classifier = DecisionTreeClassifier()
             classifier.fit(X_imputed, y)

             # Transform the single sample using the imputer
             single_sample_imputed = imputer.transform(single_sample[:, :-1])

             # Predict the outcome for the single sample
             prediction = classifier.predict(single_sample_imputed)
             pred_prob = classifier.predict_proba(single_sample_imputed)
        if prediction == 1:
            st.warning("Positive Risk-{}".format(prediction[0]))
            pred_probability_score = {"Negative DM": pred_prob[0][0] * 100, "Positive
DM": pred_prob[0][1] * 100}
            st.subheader("Prediction Probability Score")
            st.json(pred_probability_score)
            st.subheader(
```

f"You are Likely to have diabetics, we estimated there is {round(pred_prob[0][1] * 100, 4)}% of chance of you having diabteics")

else:

st.success("Negative Risk-{}".format(prediction[0]))

pred_probability_score = {"Negative DM": pred_prob[0][0] * 100, "Positive DM": pred_prob[0][1] * 100}

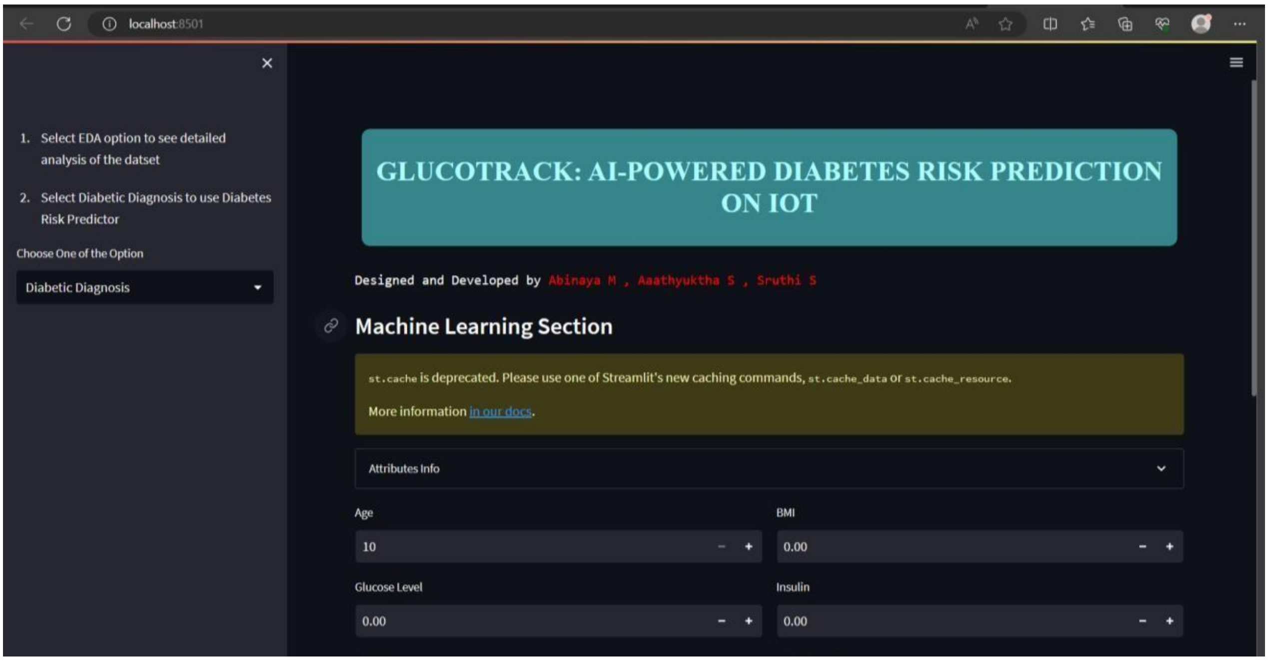
st.subheader("Prediction Probability Score")

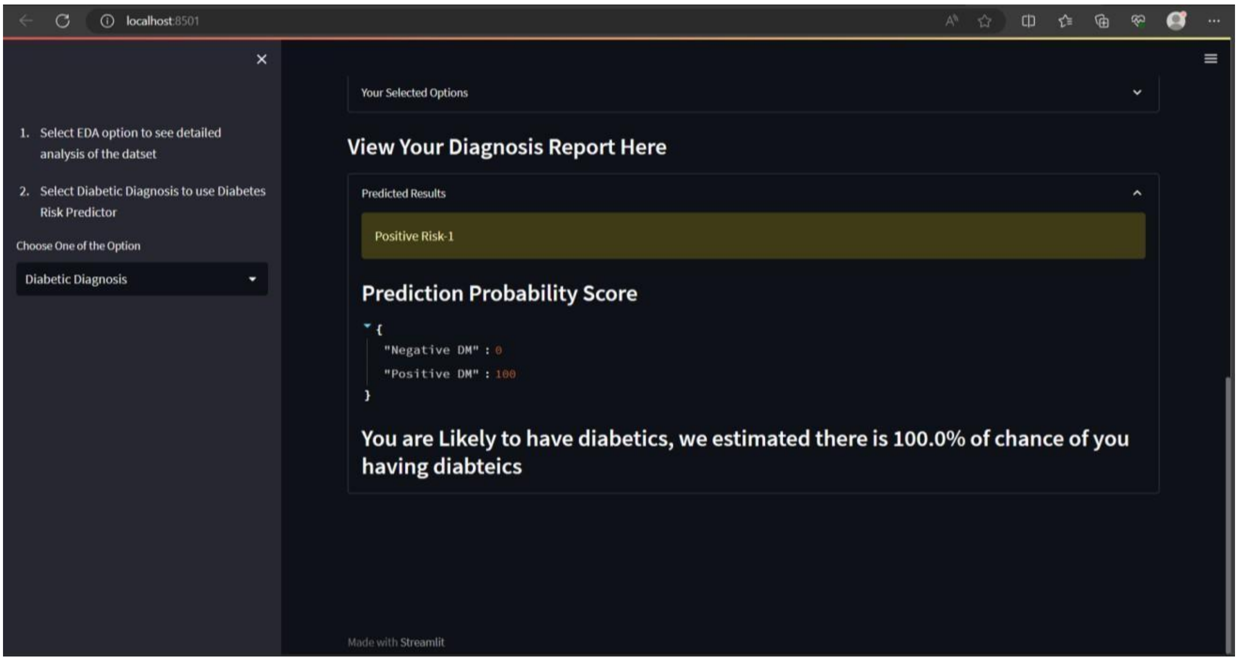
st.json(pred_probability_score)

st.subheader(

f"Woohoo!, You don't have a risk of diabetics, but we estimated there is {round(pred_prob[0][1] * 100, 4)}% of chance of you having diabteics. Be Careful ! Take Care! ")

RESULT


localhost:8501
1. Select EDA option to see detailed analysis of the datset
2. Select Diabetic Diagnosis to use Diabetes Risk Predictor
Choose One of the Option
Diabetic Diagnosis
GLUCOTRACK: AI-POWERED DIABETES RISK PREDICTION ON IOT
Designed and Developed by Abinaya M , Aaathyuktha S , Sruthi S
Machine Learning Section
st.cache is deprecated. Please use one of Streamlit's new caching commands, st.cache_data or st.cache_resource.
More information in our docs.
Attributes Info
Age
10
BMI
0.00
Glucose Level
0.00
Insulin
0.00


localhost:8501
1. Select EDA option to see detailed analysis of the datset
2. Select Diabetic Diagnosis to use Diabetes Risk Predictor
Choose One of the Option
Diabetic Diagnosis
Your Selected Options
View Your Diagnosis Report Here
Predicted Results
Positive Risk-1
Prediction Probability Score
{
"Negative DM" : 0
"Positive DM" : 100
}
You are Likely to have diabetics, we estimated there is 100.0% of chance of you having diabteics
Made with Streamlit

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