GlucTeleAI: ML-assisted Preliminary Diabetes Assessment Framework for Telemedicine Systems

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***Abstract*—The healthcare industry is experiencing a radical transition in this age of fast technology innovation, with telemedicine emerging as a significant paradigm. Telemedical techniques have become more widespread, including teleprescription for delivering medicine to remote locations and telesurgery for performing surgical operations from a distance. Tele-diabetes checks are an essential element for physicians in this setting. We present a sophisticated framework *GlucTeleAI* that utilizes Machine Learning (ML) to accurately evaluate pre-diabetes such as Decision Tree, Random Forest, K-Nearest Neighbour, Logistic Regression, Naive Bayes, and Support Vector Machine. This comprehensive evaluation guarantees the effectiveness of the system in precisely detecting diabetic patients inside the telemedicine setting, establishing the basis for improved remote healthcare treatments. The performance of models is thoroughly assessed using essential measures such as accuracy, F1-score, recall, and precision. The performance evaluation includes metrics such as precision-recall, receiver operating characteristic (ROC) curve, and confusion matrix. *GlucTeleAI* considerably improves the advancement of telehealth and establishes the basis for improved standards in remote healthcare.**

Index Terms*—Telemedicine, Teleprescription, Diabetes, Machine Learning

I. Introduction

Telemedicine has gained significant popularity because it addresses an essential gap in modern healthcare. The term telemedicine originates from the Latin words medicine (meaning healer or physician) and tele (meaning at a distance). The persistent challenge emerges from the unbalanced proportion of the expanding patient population to the limited number of medical staff. Insufficient resources for the healthcare industry combined with the country's rapid population expansion exacerbates this issue, perhaps leading to a lack of diagnosis and treatment. Patients who require medical care from remote locations, especially when regular healthcare services are challenging to access. The utilization of telemedicine has experienced substantial adoption, with 80% of individuals having utilized it at least once. Telemedicine, therefore, is a crucial medical application in circumstances where getting medical treatment can be challenging [1]. Noteworthy development has been observed among certain demographic groups, including a 12% increase in acceptance among individuals aged 55 and above and a 13% rise in the use of telemedicine among rural populations [2]. Apart from the growing popularity of telemedicine, an array of barriers persist, including video compression, service quality, data security, and scheduling.

Telemedicine is a significant resource for remotely assessing and managing a wide range of medical diseases, including chronic diseases like diabetes, heart issues, and osteoporosis. Diabetes, characterized by impaired insulin synthesis, benefits significantly from the capabilities of telemedicine in facilitating remote healthcare interventions and monitoring. Approximately 10.5% of adults aged 20-79 have diabetes, and 50% are unaware that they are living with the condition. The International Diabetes Foundation (IDF) has anticipated by 2045, there will be 783 million people living with diabetes, which represents a 46% rise. The consequences of failing to detect, recognize, or delay the treatment for diabetes conditions can be potentially catastrophic.

Access to medical care and detection of diabetes are therefore crucial. Telemedicine in diabetes enables the physician to provide suitable treatments for the diagnosis. Patients with diabetes are benefited from efficient methods for life-saving healthcare services [3]. Anesthesia can potentially be catastrophic, for example, if the patient has diabetes and the doctor is not informed of such. Through the combination of telemedicine with a comprehensive understanding of diabetes, one can effectively mitigate such occurrences and perhaps prevent fatalities. The Finnish Diabetes Prevention study affirmed the significance of lifestyle therapy in diabetes prevention, complementing the Diabetes Prevention Program's (DPP) confirmation of metformin's preventive benefits alongside lifestyle modifications. To bridge these findings into telemedicine, researchers employ digital techniques, constituting the Digital Diabetes Prevention Program (d-DPP), to enhance the application of preventive strategies through remote, technology-driven interventions [4].

Ensuring that there is provision of medical treatment and quick identification of diabetes is of utmost importance, emphasizing the crucial need for efficient healthcare solutions. Telemedicine is a game-changer when it comes to this issue; it allows physicians to use remote monitoring and diagnostics to provide patients with treatments that are specific to their needs. By leveraging this cutting-edge methodology, healthcare provision is not only rendered more effective but proactive interventions for diabetes management are also enabled. Numerous researchers have offered different approaches to address this significant health concern, acknowledging its severity. In the paper by Borries *et al.*, lower HbA1c levels were indicated with the use of telemedicine for self-management in diabetic patients [5]. Efficacy of telemedicine on glycaemic control in patients with type 2 diabetes, improved QoL scores have been seen, along with other positive health outcomes are claimed by Groot *et al.* [6].

The fundamental remoteness of telemedicine creates the possibility of pharmaceutical prescription errors, particularly when it comes to diabetes management. As previously stated, diabetes demands comprehensive evaluation and precise medical therapies. Precise medication prescriptions and continuous assessment-informed personalized adjustments are essential due to the complex nature of the condition. In addition to offering beneficial remote healthcare, telemedicine emphasizes the need for strong diagnostic procedures to guarantee the accuracy needed for diabetes control, reducing the possibility of inaccurate test findings or unfavorable medication combinations. Our innovative framework of *GlucTeleAI* comprises using machine learning (ML) models such as Decision Tree (DT), Random Forest (RF), K-Nearest Neighbour (KNN), Logistic Regression (LR), Naive Bayes (NB), and Support Vector Machine (SVM). The main goal is to improve the accuracy and robustness of remote disease prediction by utilizing the advantages of current data from adjacent domains through the use of these models. The efficacy of prediction accuracy in the domain of remote healthcare evaluations is enhanced through the integration of multiple ML techniques.

A. Research Contributions

The paper discusses significant modifications in the field of diabetes remote detection through the utilization of an ML-based methodology.

- This accomplished approach seamlessly integrates comprehensive patient data monitoring for telemedicine and telesurgery. We present an ML model *GlucTeleAI* that incorporates patient health data such as blood pressure measurements, cholesterol levels, and cardiac history.
- The ML models are thoroughly assessed using a DT, RF, KNN, LR, NB, and SVM.
- The evaluation process involves a thorough examination of various training preferences, accuracy measurements, loss curves, and performance metrics including recall, and precision. This ensures that a teleprescription system for diabetes is both effective and reliable.

B. Organization of the Paper

The rest of the paper is organized as follows. Section II covers the existing research and Section III presents a detailed description of the proposed system. Section IV subsequently offers an assessment of the performance of the proposed system. Finally, the research concludes by presenting prospects in Section V.

II. Related Work

The objective of this research is to improve the efficiency and efficacy of teleprescription and telemedicine for diabetes by using a complete approach. By combining IoT-based healthcare with advanced AI systems, we hope to make diabetes predictions more accurate, especially during surgery and anesthesia. The chosen research papers examine the intricate uses of telemedicine for diabetes, investigating the convergence of telepharmacy and teleprescription, with a particular emphasis on the difficulties and possibilities that arise during the COVID-19 epidemic. Above in the introduction, we discussed [5] [6] in which researchers predict diabetes in patients by various parameters. The papers related to telemedicine and diabetes are reviewed below.

Sowah *et al.* [7] in their paper have discussed implementing software systems to improve diabetes management using ML. Integrating AI, and the IoT into telemedicine has been discussed by Jheng *et al.* [8]. The revolution of technological changes driven by IoT and ML has improved the healthcare sector with deep roots in telemedicine a suggested approach by Kumari *et al.* [9]. The research conducted by Guadamuz *et al.* [10] examines the connection between telepharmacy and medication adherence in urban areas. The results suggest that those utilizing telepharmacy services exhibited lower levels of medical adherence compared to those using conventional pharmacy services. Guadamu *et al.* [11] indicating that the recent COVID-19 pandemic compelled us to begin tele-prescription to regulate glycemic levels in diabetic patients. Increased use of telemedicine, mobile applications, and AI, streamlined the process of managing psoriasis [12]. An approach to developing a teleconsultation system for tertiary care hospitals in India to accommodate facilities like video calling consultation, incorporating EHR-compliant clinical prescription, while exploring EHR management and cloud-based services leveraging 5G to create enhanced Quality of Service (QoS) and user experience, Ranjan and Aravindakshan [13]. Mutual telemedicine consultations give an advantage for better diabetic self-care, lessen the burden of treatment, and elevate psychosocial outcomes in patients diagnosed with type 2 diabetes by David *et al.* [14].

The novel methodology we utilize leverages predictive analytics to effectively forecast the manifestation of diabetes, thereby facilitating timely intervention along with customized medication recommendations even in remote circumstances. Our method enables physicians to evaluate the need for teleprescription in the treatment of diabetes, therefore promoting well-informed decision-making and efficient healthcare operations by ML. The adoption of this technological framework improves simultaneously the accuracy of diagnoses and the efficiency of healthcare operations in the telemedical environment.

III. The Proposed Scheme

In the proposed approach which is presented in Fig. 1, the three key layers Data Acquisition layer, AI layer, and Clinical Managerial layer are meticulously designed to enhance the adaptability and accuracy of *GlucTeleAI*.

A. Data Acquisition Layer

In the Data Acquisition Layer, the raw data (X_{raw}) as expressed in Eq. 1. It contains a total of 21 features, including direct participant responses and computed variables. In the context of diabetes computation, the features such as blood pressure, cholesterol, BMI, and other relevant factors are symbolically represented as $x_1, x_2, \ldots, x_{21}$. Each x_i corresponds to a specific feature, with x_1 denoting blood pressure calculated by a sphygmomanometer, x_2 representing cholesterol which is measured by cholesterol testing machine, x_3 for BMI by BMI scale, and up to x_{21} for the 21st feature which includes all the records of previous medical, physical and general health reports. The input variables in mathematical models are depicted by these representations, which aid in the analysis and prediction of diabetes using the provided set of features.

$$X_{\text{raw}} = (x_1, x_2, \ldots, x_21) \tag{1}$$

Every symbol x_i in this data has intricate semantics. To improve the robustness and balance of the dataset, techniques for preprocessing such as Standard Scaling and SMOTE-ENN have been employed. Standard Scaling, denoted by the function f_{scale}, involves transforming the raw feature set X_{raw} to X_{scaled} using the StandardScaler in Eq. 2. The process of normalization and standardization of numerical features is performed using the StandardScaler method.

$$X_{\text{scaled}} = f_{\text{scale}}(X_{\text{raw}}) \tag{2}$$

Afterward, to eliminate class imbalances, the Synthetic Minority Over-sampling Technique with Edited Nearest Neighbors (SMOTE-ENN) is implemented to produce synthetic samples in the interest of achieving a more balanced distribution. The resulting balanced feature set is denoted as X_{balanced} and is accompanied by the corresponding target variable y_{balanced} in Eq. 3.

$$X_{\text{balanced}}, y_{\text{balanced}} = \text{SMOTE-ENN}(X_{\text{scaled}}, y) \tag{3}$$

The source data undergoes meticulous preparation, enhancing its quality and usefulness for further analysis. In the initial phase of data extraction, imputation or elimination is employed to handle missing values in the dataset. Feature selection is used to maintain important factors and reduce redundant and less informative variables. Potential outliers are addressed to prevent them from affecting the analysis and training of the model.

$$X'_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j} \tag{4}$$

where:

- X'_{ij} is the standardized value of the j^{th} feature in the i^{th} sample.
- X_{ij} is the original value of the j^{th} feature in the i^{th} sample.
- μ_j is the mean of the j^{th} feature across all samples.
- σ_j is the standard deviation of the j^{th} feature across all samples.

Consequently, by following the above-mentioned processes, we obtained the preprocessed dataset ($X_{\text{pre-processed}}$), due to which a refined foundation for the following layers is achieved.

B. GlucTeleAI layer

The *GlucTeleAI* layer is the most crucial component of the architecture framework. The primary goal is to analyze health indicators and provide personalized and efficient healthcare recommendations. In this layer, a variety of variables are taken into account for training, as a result of which the framework for health prediction and decision-making is effective and robust.

This Layer involves working on the raw data [15]. The data is derived from the Behavioral Risk Factor Surveillance System (BRFSS) 2021, which is an ongoing telephone survey conducted by the Centers for Disease Control and Prevention (CDC) in the United States. The dataset is accessed through Kaggle, and it includes responses from 438,693 individuals, who are 18 years of age or above and live in the United States. Three classes (**C**) no diabetes, prediabetes, and diabetes as denoted as 0,1, and 2.

Classical ML models are employed to analyze an extensive array of health-related attributes essential for anticipating and managing diabetes-related concerns. The ML models utilized for the predictive model are DT, NB, LR, SVM, KNN, and RF. DTs employ a recursive process of dividing datasets into uniform subsets to make decisions. At each level, they assess the characteristics and choose the most advantageous division for purity. This procedure continues until a specific depth or degree of purity is achieved. DTs are highly configurable and convenient and have outperformed other algorithms, particularly in instances with non-linear connections or intricate interactions between characteristics and the target variable.

The key components of the DT algorithm include splitting criteria, entropy, and impurity measures. The splitting criteria are used to find the method that partitions the dataset X, taking into account a chosen feature. It considers the impurity of the resulting subsets X_i following the split described in Eq. 5.

$$Q(X, \text{feature}) = \sum_{i=1}^{k} p_i \cdot \text{Impurity}(X_i) \tag{5}$$

The main objective is to determine the split that reduces impurity to the greatest extent, which results in more uniform subsets.

$$Q(X, \text{feature}) = Q(X_{\text{left}}, \text{feature}) + Q(X_{\text{right}}, \text{feature}) \tag{6}$$

The DT model splits the dataset X into subsets X_{left} and X_{right} based on the selected feature, iteratively which

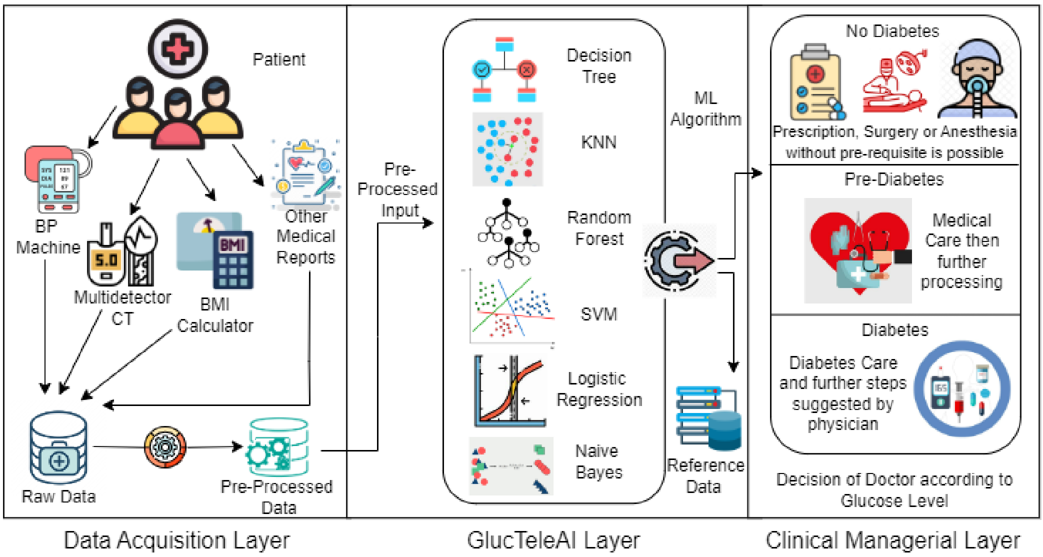


Fig. 1: The proposed approach.

is mentioned in Eq. 6. The process persists till a stopping condition is satisfied. The tree generates leaf nodes after the completion of splitting. The majority class of the samples in a leaf node is usually the expected value for that node in classification tasks.

The impurity measure (Impurity) depends on the gini impurity measure mentioned in 7. Gini impurity measures the probability of misclassifying a randomly selected element in the dataset. A lower Gini impurity value suggests a node with a higher level of purity.

$$\text{Gini}(X) = 1 - \sum_{i=1}^{k} (p_i)^2 \tag{7}$$

As described in Eq. 8, Entropy is another metric used to measure the likelihood of misclassification. It calculates the level of ambiguity within a group of samples. Similar to Gini Impurity, the objective is to minimize entropy for uniform generation of subsets.

$$\text{Entropy}(X) = -\sum_{i=1}^{k} p_i \cdot \log_2(p_i) \tag{8}$$

For model evaluation, we consider the following metrics:

$$\mathbf{Acc} = \frac{\sum_{c_i \in \mathbf{C}} \text{TPs}_{c_i}}{\sum_{c_i \in \mathbf{C}} (\text{TPs}_{c_i} + \text{FPs}_{c_i} + \text{TNs}_{c_i} + \text{FNs}_{c_i})} \tag{9}$$

$$\mathbf{Prc} = \frac{\sum_{c_i \in \mathbf{C}} \text{TPs}_{c_i}}{\sum_{c_i \in \mathbf{C}} (\text{TPs}_{c_i} + \text{FPs}_{c_i})} \tag{10}$$

$$\mathbf{Rcl} = \frac{\sum_{c_i \in \mathbf{C}} \text{TPs}_{c_i}}{\sum_{c_i \in \mathbf{C}} (\text{TPs}_{c_i} + \text{FNs}_{c_i})} \tag{11}$$

$$\mathbf{F1-Score} = 2 \times \frac{\mathbf{Prc} \times \mathbf{Rcl}}{\mathbf{Prc} + \mathbf{Rcl}} \tag{12}$$

In micro-averaging all True Positives (TPs), True Negatives (TNs), False Positives (FPs), and False Negatives (FNs) for each class ($\mathbf{C}$) are summed up and then the average is taken. Here in Eq. 9, 10 , 11, and 12 accuracy is denoted as $\mathbf{Acc}$, precision is mentioned as $\mathbf{Prc}$, recall is expressed as $\mathbf{Rcl}$ and F1-score is denoted as $\mathbf{F1-Score}$ respectively. These metrics collectively provide insights into the model's ability to correctly classify instances and balance between precision and recall.

C. Clinical Managerial Layer

The Clinical Managerial Layer is the key component that processes the outputs from *GlucTeleAI* Layer and produces practical insights based on the dataset. The primary objective of this layer is to assess the extent of diabetes problems and provide guidance for subsequent interventions. The output information of models encompasses predictions about the diabetes risk levels that are derived from the trained ML models.

The severity classification (Φ) is significant in informing appropriate healthcare responses and interventions. It is mathematically defined as :

$$\Phi = \begin{cases} 0, & \text{if no diabetes } (\phi = 1) \\ 1, & \text{if prediabetes } (\phi = 2) \\ 2, & \text{if diabetes } (\phi = 3) \end{cases} \tag{13}$$

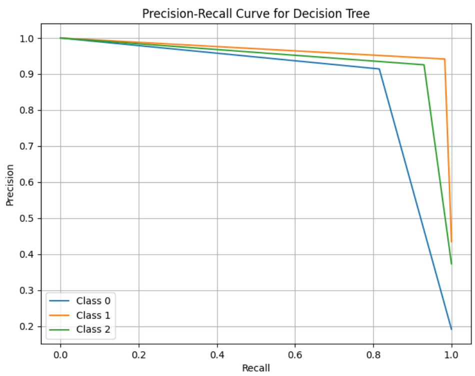
The above equation is significant because it plays a crucial role in coordinating timely and focused interventions, which are determined by the projected severity of diabetic problems. This classification system assists healthcare professionals and individuals in efficiently managing and addressing potential health hazards.

This Layer is crucial in the healthcare system as it ensures that forecasts are effectively transformed into practical and actionable knowledge. The severity assessment offered by Eq.

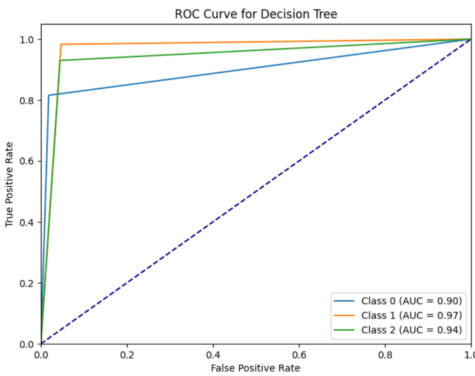
13 enables a proactive and tailored approach to diabetes care, enabling timely medication interventions and lifestyle modifications. Incorporating ML predictions into decision-making processes enhances the overall efficacy of the healthcare plan in addressing issues associated with diabetes.

IV. Performance Evaluation

This section discusses the evaluation of different ML frameworks' performance. As we discussed earlier ML models like DT, NB, LR, SVM, KNN, and RF are used to predict diabetes for the application of telemedicine. The thoughtful consideration and selection of a suitable model are critical in attaining the principal aim of our research paper, as it has a substantial impact on the quality of results. Here, the focus is to classify patients into three distinctive categories: class 0 refers to persons who do not have diabetes or only experience diabetes during pregnancy, class 1 represents individuals in a pre-diabetic condition, and class 2 identifies those who have been diagnosed with diabetes. The DT's impressive performance, shown by its visual representations, establishes it as reliable and insightful for classifying tasks. The precision-recall curve



(a) Precision-Recall Curve



(b) ROC Curve

Fig. 2: (a) Trade-off between precision and recall of Decision Tree, (b) Receiver Operating Characteristic curve of Decision Tree

is an essential component that has a significant impact on the overall evaluation of the performance of the classification approach, especially when dealing with imbalanced datasets. The precision-recall curve tells us about the trade-off between precision and recall. The AUC being higher signifies the model is robust, has high precision, and has desirable recall rates. From Fig. 2a, shows the advantages of the DT model in establishing an appropriate equilibrium between precision and recall, confirming its legitimacy as an appropriate option for classification objectives.

ROC curve helps to evaluate the performance of the classification method. On the y-axis, the true positive rate is plotted, while on the x-axis, the false positive rate is taken. When the AUC is greater than 0.5 and tends to 1.0, it is considered a desirable outcome. In Fig. 2b the AUC of DT for class 0 is 0.90, for class 1, it is 0.97, and for class 2, it is 0.94. These results, indicative of minimal false-positive rates, underscore the model's precision and reliability in accurately discerning the distinct classes within our dataset.

The confusion matrix in Fig. 3 is a 3×3 matrix for classes 0,

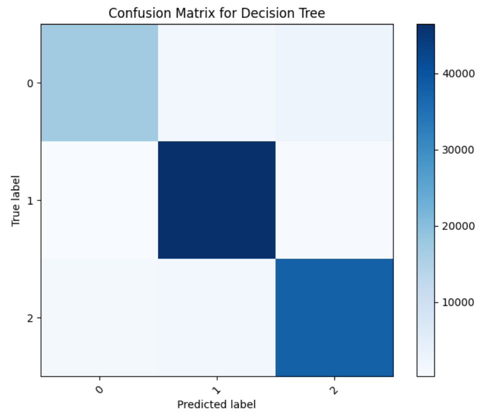


Fig. 3: Confusion matrix for Decision Tree

1, and 2. The confusion matrix serves as a detailed analytical tool, presenting a tabular breakdown of a classification model's predictive performance. Comprising true positive (correctly predicted positive instances), true negative (correctly predicted negative instances), false positive (incorrectly predicted positive instances), and false negative (incorrectly predicted negative instances), it provides a nuanced assessment of the model's proficiency. Observing the confusion matrix reveals a notable disparity in the distribution of instances among the three classes, with class 1 exhibiting a higher count than classes 0 and 2. This detailed research highlights the need for specific enhancements in the DT model's ability to accurately classify cases, particularly those belonging to class 1.

Fig. 4 shows statistics about comparisons between different models used in the paper based on parameters which is represented in Table I. Precision provides an understanding of the quality of positive predictions made by the model, while recall is the measure of the quantity, and gives insight into how truly it identifies the target, F1 score is a measure of the harmonic

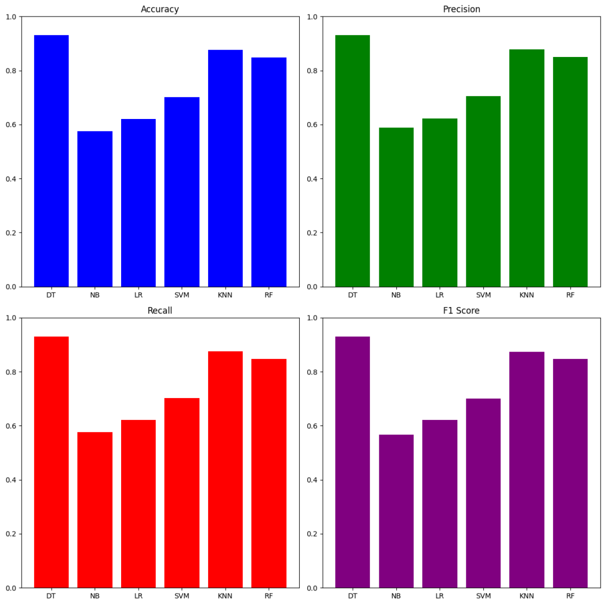


Fig. 4: Accuracy, Precision, Recall, and F1-Score Comparison for all ML-models

mean of precision and recall, and accuracy is the measure that tells about how often the machine has correctly predicted the outcome. DT stands out as the top performer, achieving an impressive accuracy of 93.08%, which makes it the optimum model to be used for the research. KNN achieves the following highest accuracy of 87.61%, making it the next best choice. It can be seen that DT performs phenomenally across all the parameters. NB has the lowest accuracy preventing it from being an economical option.

TABLE I: Performance Metrics of Machine Learning Models

Model	Accuracy	Precision	Recall	F1 Score
Decision Tree	0.9309	0.9304	0.9309	0.9299
Naive Bayes	0.5760	0.5876	0.5760	0.5672
Logistic Regression	0.6210	0.6225	0.6210	0.6211
Support Vector Machine	0.7021	0.7058	0.7021	0.7013
K-Nearest Neighbour	0.8761	0.8787	0.8761	0.8733
Random Forest	0.8473	0.8509	0.8473	0.8467

V. CONCLUSION

This paper proposes an ML-based method for remotely predicting diabetes. The main goal of the suggested *GlucTeleAI* is to provide precise outcomes for telemedicine to physicians. Through the process of training the ML model to classify data obtained from various medical devices as either manipulated or non-manipulated, we have successfully developed a reliable and efficient approach for detecting possible data tampering. The Suggested Model Decision Tree obtains an accuracy of around 93.09%. In the telemedicine environment, precise diagnostic insights are crucial for remote healthcare treatments, making accurate pre-diabetes assessments of the highest significance. Our comprehensive evaluation method includes key metrics such as accuracy, F1-scores, recall, and precision. In the future, we will include ensemble technologies to enhance the quality of diabetes prediction. Future research could explore integrating ensemble learning methods along with real-time physiological data streams to improve the accuracy and responsiveness of remote diabetes prediction, laying strong ground for telemedicine interventions.

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