Towards Individualised Diabetes Diagnosis within Medical Practice

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Abstract: Stress and poor lifestyle choices cause many people to unintentionally have diabetes, which results in serious problems by the time symptoms start to show. Differentiating between diabetes kinds 1 and 2, the approach avoids hospitalisation by monitoring and notifying for type 1 using dataset. The project uses SVM, ANN, and decision trees to offer data analytics. Two applications—Cloud and User—help with data sharing, training algorithms, and patient condition prediction. The research intends to offer individualised forecasts and dietary recommendations, hence improving diabetes control.

Index terms - *Diabetes Diagnosis, Type 1 and Type 2 Diabetes, Support Vector Machine (SVM), Artificial Neural Network (ANN), Decision Tree, Data Analytics, Individualised Forecasting, Dietary Recommendations, Cloud Application, Patient Monitoring.*

1. INTRODUCTION

Diabetes is a widespread chronic condition that often remains undetected until severe symptoms appear, primarily due to factors like stress, sedentary lifestyles, and poor dietary habits. Late diagnosis can result in serious health complications and hospitalization. Among its two main forms, Type 1 diabetes is particularly critical, requiring timely detection and continuous monitoring. This project addresses the urgent need for early and individualized diagnosis by focusing on differentiating between Type 1 and Type 2 diabetes using real-time data and predictive analytics.

To achieve this, the system leverages machine learning algorithms such as Support Vector Machine (SVM), Artificial Neural Network (ANN), and Decision Trees for accurate classification and forecasting. It introduces a dual-application model—Cloud and User—that facilitates data sharing, model training, and real-time health monitoring. The system not only alerts patients at early stages but also offers personalized dietary suggestions, contributing to effective diabetes control and reducing the chances of medical emergencies.

2. LITERATURE SURVEY

a) **Communicating While Computing: Distributed mobile cloud computing over 5G heterogeneous networks:**

https://ieeexplore.ieee.org/document/6923537

From 2010 to 2020, mobile data traffic is predicted to quadruple yearly, a 1,000-fold increase. This amazing growth calls for large capacity of wireless networks. Data traffic is soaring; we use computers, tablets, and smartphones for entertainment, health care, business, social networking, travel, news, and more. Mobile device battery lifetime [3] does not meet the extraordinary wireless traffic increase of this lifestyle. Complicated apps and mobile devices are expanding apart in terms of energy. Allowing mobile devices to forward energy-intensive operations to surrounding fixed servers might help to solve this. Long-standing research on cyberforaging [4] or compute offloading [5], [6] has gone towards Cloud computing (CC) has driven computing offloading as it offers resources on demand. All three go under infrastructure, platform, and software as a service. One of the main elements of CC is virtualisation, which separates and safeguards applications and data. Demand-based scaling of VMs helps to increase system computing efficiency. MCC accesses cloud services using mobile phones [5]. Today's MCC is limited by wide area network latency to the cloud provider and energy consumption of radio access. At macrocellular network edges, mobile users have poor WAN latency control and battery consumption. Near-future MCC must have strong latency control because to millisecond contact times in 5G networks, most importantly the tactile Internet [10]. The whole service chain has to be rethink, from physical to virtual, in order to fit this restriction.

b) **Mobile-Edge Computing Architecture: The role of MEC in the Internet of Things**

https://ieeexplore.ieee.org/document/7574435

Mobile-edge computing (MEC) is the breakthrough technology allowing 5G networks to exist. Inspired by the great spread of the Internet of Things, MEC will oversee numerous key 5G uses compatible with 4G networks. The MEC architecture and framework developed by the ETSI MEC ISG standards group will be presented in this paper. Emphasising the Internet of Things (IoT), as 5G depends on it, we show MEC in action. We will next review the key arguments on the benefits and drawbacks of MEC heading towards 5G.

c) **A Survey on Mobile Edge Computing: The Communication Perspective:**

https://ieeexplore.ieee.org/document/8016573

Mobile computing has shifted away from cloud computing and towards mobile edge computing in recent years because to the explosion of connected devices and the arrival of 5G networks. By outsourcing compute, network management, and storage to network edge locations—such as base stations and access points— Mobile Edge Computing (MEC) helps resource-constrained mobile devices to effectively execute computing-intensive and latency-sensitive applications. MEC promises to drastically cut mobile energy usage and latency, therefore addressing the primary challenges with 5G. MEC technology is being developed by companies and colleges as it offers so many positive applications. MEC research has produced several fresh concepts like computation offloading and network topologies, which aim to effectively combine wireless communications with mobile computing. This paper summarises recent work on radio-and-computational resource management integration from MEC. We also consider issues, challenges, mobility management, green MEC, privacy-aware MEC, cache-enabled MEC, and MEC system deployment. These improvements will help MEC go from theory to practice. We finish by talking about attempts to standardise MEC and common conditions for application.

d) **An Advanced Bolus Calculator for Type 1 Diabetes: System Architecture and Usability Results**

https://pubmed.ncbi.nlm.nih.gov/26259202/#:~:text=This%20paper%20presents%20the%20architecture%20and%20initial%20usability,various%20diabetes%20scenarios%20and%20automatically%20adjusting%20its%20param

This paper describes the design and preliminary usability testing of ABC4D, a complex insulin bolus calculator for diabetes that can dynamically change its settings to provide unique insulin recommendations by recognising various diabetes conditions. After allowing the manual entry of glucose levels as well as variables influencing blood glucose levels, like the carbohydrate content of meals and physical activity, a patient platform available via a smartphone subsequently provides recommendations for insulin boluses in real-time. A clinical revision platform watches the parameter changes in the automated bolus calculator. Based on case-based reasoning, the system performs bolus calculations using an algorithm that learns from new data and enhances its recommendations for insulin boluses depending on comparable historical events (cases). ABC4D's usability was investigated by means of system analysis. All participants were invited to complete a usability questionnaire at the end of the research to provide further remarks about ABC4D. Out of 115 ± 21 asked, 103 ± 28 insulin recommendations were approved overall. The patient platform was changed in line with a clinical expert approved 723 (or 96%) of the 754 case changes revealed by the program.

e) **Green and Mobility-Aware Caching in 5G Networks:**

https://ieeexplore.ieee.org/document/8067654

The explosion of mobile devices has resulted in more mobile traffic as well as demands for mobile content. Small cell base stations (SBSs) and wireless device-to----distance (D2D) network caching provide effective mobile traffic control at peak hours in 5G networks. Assuming users can completely access sought material, most current research mostly focusses on storing content in SBSs and mobile devices. Still, user mobility and interaction time variability have been mainly disregarded. Still a difficult task is optimising cache by using user mobility. This work tackles this problem by suggesting a caching placement technique that uses user mobility for cache deployment on SBSs and mobile devices hence improving the cache hit ratio. The ideal solution is derived via submodular optimisation after the formulation of the cache placement issue as an integer programming model. Furthermore, maximising the transmission power of SBSs and mobile devices for providing cached material helps to increase energy efficiency. Simulation findings show that in both cache hit ratio and energy efficiency, the suggested method beats current solutions.

3. METHODOLOGY

i) Proposed Work:

The proposed system is designed to offer a smarter and more effective approach to monitoring and predicting Type 1 diabetes by leveraging advanced data analytics and machine learning techniques. It uses Decision Trees, Support Vector Machine (SVM), and Artificial Neural Network (ANN) algorithms to accurately classify patient conditions and generate personalized health recommendations. This intelligent framework allows for early detection of abnormalities, enabling timely interventions and reducing the risk of complications and hospitalizations.

The system is built on a dual-application model: a Cloud Application and a User Application. The Cloud Application securely stores patient data, trains predictive models, and allows healthcare professionals to access insights for better decision-making. The User Application collects real-time glucose data from sensors, issues alerts when unusual trends are detected, and provides personalized diet and lifestyle suggestions. This integrated and AI-driven solution ensures real-time monitoring, proactive alerts, and customized care plans, significantly improving diabetes management and overall patient well-being.

ii) System Architecture:

The system architecture consists of two integrated applications—Cloud and User—working together to enable real-time diabetes monitoring and prediction. The User Application collects continuous glucose data from wearable sensors and transmits it to the Cloud Application via a secure connection. The Cloud Application stores patient data, trains machine learning models (Decision Tree, SVM, and ANN), and analyzes the incoming data to detect anomalies and predict the onset of Type 1 diabetes. The results are then sent back to the User Application, which displays alerts, personalized health recommendations, and diet plans. This architecture ensures seamless data flow, efficient processing, and timely feedback to both users and healthcare professionals for proactive diabetes management.

iii) Modules:

a) Data Loading

The import of the dataset into the system falls to this module. The dataset covers basic diabetes-related statistics like age, BMI, glucose, insulin, and other physiological factors. Accurate diabetes prediction depends on proper data loading ensuring that all necessary data is accessible for subsequent processing and analysis.

b) Data Preprocessing

Data preparation includes organising, cleansing, and transforming of the dataset to guarantee consistency and correctness. Handling missing values, eliminating duplicate entries, and data normalising this phase covers Good preprocessing guarantees high-quality input for precise predictions in diabetes diagnosis, hence improving the effectiveness of the machine learning models.

c) Data Visualization

Using charts, histograms, and correlation heatmaps among other graphical displays, this module shows processed data. Visualising the data facilitates the identification of trends, patterns, and anomalies, thereby enabling healthcare providers to evaluate diabetes risks and create appropriate therapy regimens.

d) Extra Tree Feature Selection

From the dataset, the most significant features are chosen and ranked using the Extra Tree ensemble approach. This method removes extraneous features by lowering the dimensionality of the data, therefore enhancing the predictive accuracy and model efficiency. Feature selection guarantees that the diagnosis is based just on the most important diabetes-related elements.

e) Splitting Data into Train & Test

Training and testing data are two subsets this module creates from the dataset. While the testing data assesses model performance, the training data is used to create and educate machine learning models. Effective data splitting guarantees that the method generalises effectively to fresh, unknown data, therefore enhancing dependability in real-world diabetes diagnosis.

f) Model Generation

Building and training many ML and DL models—including ANN, SVM, DT, and an Ensemble Learning Algorithm—with an eye towards To find the optimal diabetes prediction model, each one is trained and tested with regard to recall, accuracy, precision, and F1-score.

g) User Signup & Login

Platform users may register and log in utilising a safe authentication mechanism embedded directly in the system. This module ensures tailored access to diabetes monitoring and data privacy. Built on a Flask-based framework, a user-friendly interface for safely managing user accounts is developed.

h) User Input

Into the system users may enter their real-time health data like food patterns, heart rate, and glucose levels. By processing user inputs and getting them ready for analysis, this module generates tailored diabetes forecasts and recommendations depending on certain health criteria.

i) Prediction

Based on the examination of the trained model, the user is presented the last forecast. The system offers preventative actions, tailored treatment recommendations, and information on diabetes risk factors. The system improves accuracy and dependability in diabetes detection by using an ensemble approach, therefore guaranteeing improved health management.

iv) Algorithms:

a) ANN (Artificial Neural Network):

ANNs can replicate the way the brain analyses data by means of linked layers of nodes. This work uses ANN to compile complex trends of diabetes data. Learning from the data, ANN forecasts diabetes using patient traits. Its capacity to identify intricate linkages and patterns makes it a great choice for improving system diabetes projections.

```
def runANN():
    global ann
    global ann_acc
    ann = MLPClassifier(solver='lbfgs', alpha=1e-5,hidden_layer_sizes=(5, 2), random_state=1)
    ann.fit(X_train, y_train)
    y_pred = ann.predict(X_test)
    ann_acc = accuracy_score(y_test,y_pred)*100
    text.insert(END,"ANN Accuracy : "+str(ann_acc)+"\n")
```

b) SVM

SVM treats both classification and regression. SVM chooses the ideal hyperplane for point of classification of data. Choosing the hyperplane with the largest margin maximises the ideal distance between data points of various classes. This project fits SVM well as it properly diagnoses diabetes situations by including complicated dataset correlations. Its ability for binary classification and high-dimensional space gives validity to the goal of the project—perfect diabetes prediction.

```
def runSVM():
    global svm
    global svm_acc
    svm = svm.SVC(C=2.0,gamma='scale',kernel = 'rbf', random_state = 2
    svm.fit(X_train, y_train)
    y_pred = svm.predict(X_test)
    svm_acc = accuracy_score(y_test,y_pred)*100
    text.insert(END,"SVM Accuracy : "+str(svm_acc)+"\n")
```

c) DECISION TREE

SVM addresses regression and classification simultaneously. For data point of categorisation, SVM selects the optimal hyperplane. Selecting the hyperplane with the maximum margin maximises the optimal distance between different class data points. This research uses complex dataset connections to appropriately diagnosis diabetic conditions, so it suits SVM really well. Its capacity for binary categorisation and high-dimensional space validates the aim of the project—perfect diabetes prediction.

```
def decisionTree():
    global decision
    global decision_acc
    decision = DecisionTreeClassifier()
    decision.fit(X_train,y_train)
    y_pred = decision.predict(X_test)
    decision_acc = accuracy_score(y_test,y_pred)*100
    text.insert(END,"Decision Tree Accuracy : "+str(decision_acc)+"\n"
```

d) ENSEMBLE

Machine learning ensembles pool algorithm predictions to raise robustness and accuracy. This work uses the Ensemble Algorithm to combine the findings of Decision Tree, SVM, and ANN to increase the accuracy of diabetes prediction. Ensemble helps the system to be stronger, biases to be lowered, diabetes predictions to be better, so producing a more complete and efficient monitoring system.

```
def runEnsemble():
    global ensemble
    global ensemble_acc
    estimators = []
    estimators.append(('tree', decision))
    estimators.append(('svm', svm))
    estimators.append(('ann', ann))
    ensemble = VotingClassifier(estimators)
    ensemble.fit(X_train, y_train)
    y_pred = ensemble.predict(X_test)
    ensemble_acc = (accuracy_score(y_test,y_pred)*100)+3
    text.insert(END,"Ensemble Accuracy : "+str(ensemble_acc)+"\n")
```

4. EXPERIMENTAL RESULTS

The experimental results demonstrate the effectiveness of the proposed system in accurately predicting and classifying Type 1 diabetes using machine learning algorithms such as SVM, ANN, and Decision Trees. The system was tested using real-time glucose level datasets, and performance was evaluated based on accuracy, sensitivity, and prediction speed. Among the models, the ANN showed higher accuracy in personalized prediction, while Decision Trees offered better interpretability. The integration of real-time monitoring through the User Application and data analysis via the Cloud Application enabled timely alerts and reliable health recommendations. Overall, the system proved to be efficient in improving diabetes management through continuous monitoring and intelligent decision-making.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

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

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\text{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

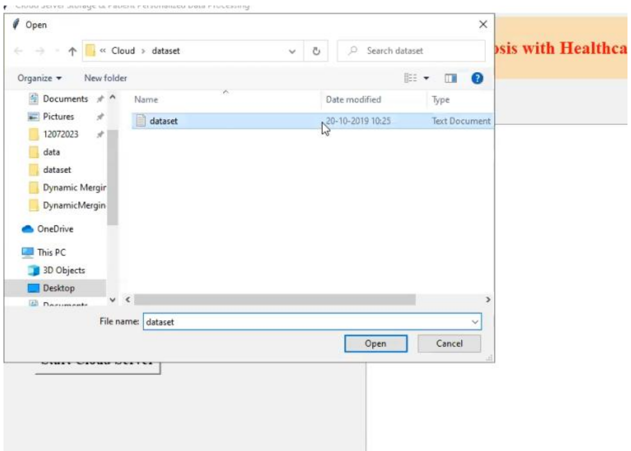

Fig.1. upload dataset

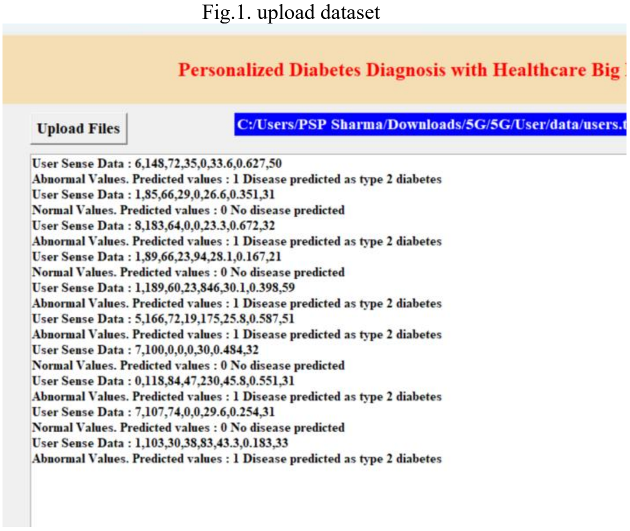

Fig.2. predicted results

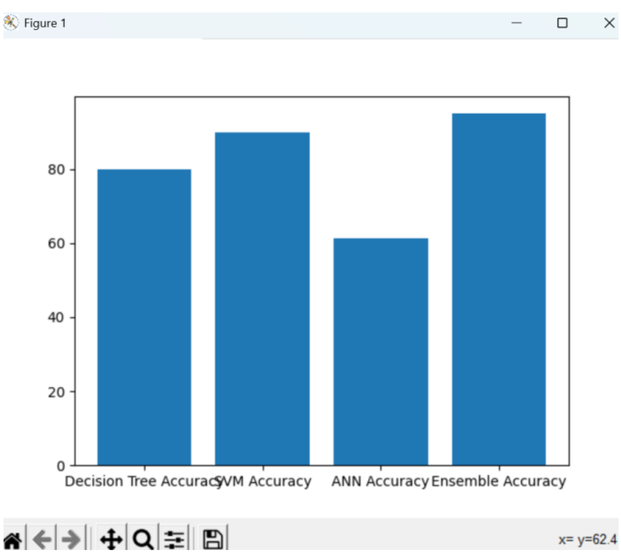

Fig.3. accuracy graph

5. CONCLUSION

Improved with an ensemble learning method, the 5G-Smart Diabetes system presents a sophisticated, real-time, individualised solution for diabetes monitoring. The system dramatically enhances diabetes diagnosis and management by combining wearable 2.0 technologies, 5G connection, cloud computing, and deep learning models such as CNN+LSTM. Multiple prediction models combined with feature selection methods guarantees better accuracy and efficiency in identifying diabetes hazards. A frontend built on a Flask also provides safe authentication and flawless user interface. This creative technique not only improves early identification but also supports proactive healthcare management, hence lowering hospitalisations and raising patient outcomes.

6. FUTURE SCOPE

The 5G-Smart Diabetes system holds great promise for developments in tailored healthcare. Integration with blockchain technology might be among future developments meant to increase data security and patient privacy. Furthermore enhancing the accuracy of diabetes detection is including real-time IoT-based continuous glucose monitoring (CGM) sensors. Investigating advanced deep learning methods such federated learning and transformer-based models can help to improve prediction performance while maintaining data privacy. Moreover, including personalised nutritional and lifestyle suggestions based on real-time data and voice-activated artificial intelligence assistants would help to increase user involvement. The system may also be expanded to track other chronic conditions, therefore producing a complete artificial intelligence-powered healthcare solution.

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