TOWARD PERSONALIZED DIABETES DIAGNOSIS WITH HEALTHCARE

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Abstract: This extended 5G-Smart Diabetes system enhances diabetes diagnosis by integrating an ensemble learning approach that combines CNN and LSTM models for improved predictive accuracy. By leveraging the strengths of deep learning, the system refines diabetes detection and provides more reliable personalized recommendations. The architecture utilizes 5G technology, wearable smart devices, and cloud computing for real-time health monitoring, ensuring seamless data collection and processing. Additionally, a Flask-based frontend is developed for user authentication, interactive testing, and easy accessibility for both patients and healthcare providers. These advancements enhance early detection, optimize treatment plans, and offer a more intelligent, user-friendly, and scalable diabetes management solution. The integration of deep learning and real-time data processing ensures a cost-effective, accurate, and sustainable approach to diabetes care.

Index terms - — *Big Data Analytics, 5G-Smart Diabetes, Ensemble Learning, CNN, LSTM, Machine Learning, Real-time Monitoring, Cloud Computing, Wearable Devices, Diabetes Prediction, Flask Framework, Personalised Healthcare..*

1. INTRODUCTION

Diabetes affects millions of people in all age groups and is a growing worldwide health concern. Conventional diabetes monitoring systems rely on manual testing, which lacks real-time data processing and can be unpleasant and error-prone. Artificial intelligence and real-time monitoring are now essential for improving diabetes diagnosis and treatment due to technological improvements. While some automation is offered by current techniques like Continuous Glucose Monitoring (CGM) and mobile health apps, they frequently fall short of providing real-time, individualized insights based on a patient's continuous physiological data.

Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models are used in the 5G-Smart Diabetes system to implement ensemble learning approaches in order to overcome these constraints. By identifying temporal and geographical relationships in physiological data, this integration increases prediction accuracy and provides a more accurate and flexible diabetes monitoring solution. The system guarantees smooth real-time surveillance of health indicators, enabling early detection and intervention, by utilizing wearable technology, cloud-based big data analytics, and 5G technology.

In order to offer an interactive and user-friendly experience, a Flask-based frontend is also implemented. This allows for real-time forecasts, safe data management, and authentication. This makes diabetes monitoring more accessible to both individuals and medical professionals. The suggested expansion guarantees a scalable, effective, and intelligent approach to individualized diabetes management in addition to increasing the accuracy and dependability of diabetes prediction.

2. LITERATURE SURVEY

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

Between 2010 and 2020, mobile data traffic is predicted to quadruple yearly, a 1,000-fold growth. Large amounts of wireless network capacity are required for this amazing breakthrough. We use computers, cellphones, and tablets for social media, business, health care, entertainment, travel, news, and more as data traffic grows. Mobile device battery endurance does not keep up with the tremendous surge in wireless traffic associated with this lifestyle [3]. The energy gap between mobile devices and complex apps is growing. This may be resolved by enabling mobile devices to transmit energy-intensive operations to adjacent fixed servers. Long-term research has been done on cyberforaging [4] and compute offloading [5], [6]. Cloud computing (CC), which offers resources on demand, has led to an increase in computer offloading. Infrastructure, platform, and software as a service are the names given to all three. A crucial part of CC is virtualization, which separates and safeguards data and applications. VMs can increase system computing efficiency by scaling on demand. Mobile phones are used by MCC to access cloud services [5]. Today's MCC is limited by the energy consumption of radio access and the latency of the wide area network to the cloud provider. WAN latency management and power consumption are subpar for mobile users at macrocellular network edges. Near-future MCC must have stringent latency management because to millisecond contact periods in 5G networks, particularly the tactile Internet [10]. The whole service chain, from physical to virtual, needs to be reconsidered in order to satisfy this restriction.

b) Mobile-Edge Computing Architecture: The role of MEC in the Internet of Things: acknowledged as a crucial enabler for 5G networks, mobile-edge computing (MEC) is an emerging technology. Inspired by the widespread use of the Internet of Things (IoT), MEC will handle several important applications of the 5G system while remaining compatible with existing 4G networks. The European Telecommunications Standards Institute (ETSI) MEC Industry Specification Group (ISG) standards group recently developed the MEC framework and architecture, which is the subject of this article's tutorial on MEC technology. Since IoT is seen as a key driver for 5G, we offer various instances of MEC implementation, with particular attention to IoT scenarios. Lastly, we go over the key advantages and difficulties of MEC's transition to 5G.

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

In recent years, mobile computing has shifted from cloud computing to mobile edge computing due to the growth of connected devices and the introduction of 5G networks. By shifting compute, network management, and storage to network edge sites like base stations and access points, Mobile Edge Computing (MEC) allows resource-constrained mobile devices to effectively execute computing-intensive and latency-sensitive applications.MEC promises to drastically reduce mobile energy usage and latency in order to address the primary issues with 5G. MEC technology is being developed by businesses and academic institutions due of its many benefits. MEC research, which aims to efficiently combine wireless communications with mobile computing, has produced a number of innovative concepts, such as computation offloading and network topologies. This article summarizes recent work by MEC on the combination of radio and computational resource management. We also examine the issues, challenges, green MEC, privacy-aware MEC, cache-enabled MEC, mobility management, and MEC system implementation. MEC's shift from theory to practice will be made easier by these improvements. We conclude by talking about initiatives to standardize MEC and typical implementation scenarios.

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

The design and first usability testing of ABC4D, a complex insulin bolus calculator for diabetes that can identify various diabetic situations and dynamically adjust its settings to provide personalized insulin recommendations, are described in this article. A smartphone-based patient platform allows users to manually enter blood glucose levels and variables that affect them, such the amount of carbohydrates in meals and physical activity. The platform then provides real-time insulin bolus recommendations. A clinical revision platform manages the parameter modifications for the automated bolus calculator. For bolus calculations, the system employs a case-based reasoning algorithm that learns from fresh data and refines its insulin bolus recommendations based on comparable historical events (cases). The usefulness of ABC4D was investigated using system analysis. All participants were requested to complete a usability questionnaire at the end of the research in order to provide additional feedback on ABC4D. Out of the 115 ± 21 insulin proposals that the participants sought, 103 ± 28 were accepted. Of the 754 case changes recommended by the clinical revision program, 723 (or 96%) were approved by a clinical expert, and the patient platform was adjusted appropriately.

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

Both mobile traffic and demand for mobile content have increased as a result of the widespread use of mobile devices. Small cell base stations (SBSs) and wireless device-to-device (D2D) network caching can help 5G networks handle mobile traffic efficiently during peak hours. Assuming users can completely access requested material, the majority of current research focuses on caching content in SBSs and mobile devices. User mobility and unpredictable interaction times, however, have received little attention. Utilizing user mobility to optimize caching is still a difficult task. In order to solve this problem, this study suggests a caching placement technique that uses user mobility for cache deployment on SBSs and mobile devices, improving the cache hit ratio. To find the best answer, submodular optimization is used to frame the cache placement issue as an integer programming model. Optimizing the transmission power of SBSs and mobile devices for caching content also improves energy efficiency. Simulation findings show that the suggested solution performs better than current methods in terms of energy efficiency and cache hit ratio.

3. METHODOLOGY

i) Proposed Work:

By incorporating ensemble learning approaches that mix CNN and LSTM models, the expanded 5G-Smart Diabetes system improves diabetes diagnosis. By efficiently capturing both spatial and temporal information from real-time physiological data, our hybrid deep learning technique increases prediction accuracy and makes it possible to identify diabetes risks early. In order to provide smooth real-time data collection and transfer to cloud-based healthcare systems, the system continually monitors vital health metrics including blood glucose levels, heart rate, and body temperature using 5G-enabled wearable smart devices. An ensemble model is used to process the gathered data, with CNN extracting significant features and LSTM handling sequential dependencies to produce more dependable and customized treatment suggestions. Furthermore, a Flask-based interface is created to provide safe data administration, interactive prediction visualization, and user authentication, improving diabetes monitoring accessibility for patients and medical professionals. The solution guarantees real-time model updates, smooth data sharing, and enhanced healthcare decision-making by utilizing big data analytics, cloud computing, and 5G connection. Through AI-driven continuous monitoring, this clever, scalable, and economical method provides a complete diabetes management solution, encouraging early intervention, individualized treatment, and improved health outcomes.

ii) System Architecture:

To improve diabetes diagnosis and treatment, the expanded 5G-Smart Diabetes system incorporates cutting-edge ensemble learning algorithms. This system uses a mix of CNN and LSTM models, which efficiently handle both spatial and temporal characteristics from real-time physiological data, in contrast to conventional techniques. By improving prediction accuracy, our hybrid deep learning method enables early identification and individualized therapy suggestions. The solution allows for smooth data transmission to cloud-based healthcare platforms and continuous health monitoring through the use of wearable smart devices and 5G technology. Three main layers make up the framework of the suggested system:

1. Sensing Layer: IoT-enabled sensors and wearable smart apparel gather physiological data in real time, including body temperature, heart rate, and blood glucose levels.

2. Personalized Diagnosis Layer: CNN+LSTM-based ensemble models are used to process the gathered data, increasing the precision of identifying various stages of diabetes and forecasting possible dangers.

3. Data-Sharing and User Interface Layer: To enable user identification, safe data access, and interactive prediction visualization, a Flask-based frontend is provided, enabling patients and healthcare professionals to make well-informed decisions.

Real-time model training, automated upgrades, and effective data exchange between patients and medical professionals are made possible by the system's integration of big data analytics and cloud computing. Additionally, several model predictions are combined using ensemble learning approaches, guaranteeing a more solid and trustworthy diagnosis. The adoption of a Flask-based web application enhances usability and accessibility even further, giving users a smooth experience.

With real-time, AI-driven tailored monitoring, the proposed 5G-Smart Diabetes system offers a scalable, economical, and intelligent healthcare solution that guarantees better disease prevention, early intervention, and improved patient outcomes.

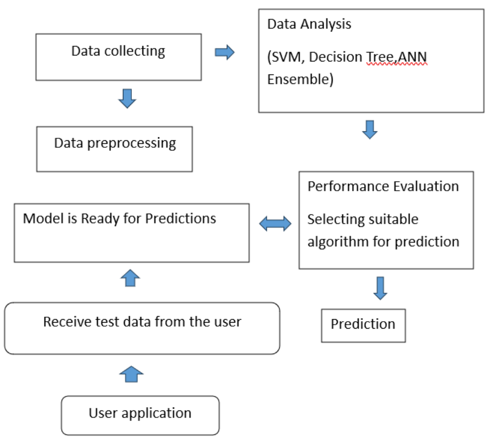

Fig1 proposed architecture

iii) Modules:

a) Data Loading

This module is responsible for importing the dataset into the system. The dataset includes essential diabetes-related information such as glucose levels, insulin levels, age, BMI, and other physiological parameters. Proper data loading ensures that all required data is available for further processing and analysis, forming the foundation for accurate diabetes prediction.

b) Data Preprocessing

Data preprocessing involves cleaning, transforming, and organizing the dataset to ensure consistency and accuracy. This step includes handling missing values, removing duplicate records, and normalizing the data. Proper preprocessing enhances the efficiency of the machine learning models, ensuring high-quality input for accurate predictions in diabetes diagnosis.

c) Data Visualization

This module presents processed data through various graphical representations, such as charts, histograms, and correlation heatmaps. Visualizing the data helps in identifying trends, patterns, and anomalies, making it easier for healthcare professionals to analyze diabetes risks and develop effective treatment plans.

d) Extra Tree Feature Selection

The Extra Tree ensemble method is used to select and rank the most important features from the dataset. By reducing the dimensionality of the data, this technique eliminates irrelevant attributes, improving model efficiency and prediction accuracy. Feature selection ensures that only the most critical diabetes-related factors contribute to the diagnosis.

e) Splitting Data into Train & Test

This module divides the dataset into two subsets: training and testing data. The training data is used to build and train machine learning models, while the testing data evaluates model performance. Proper data splitting ensures that the system generalizes well to new, unseen data, improving reliability in real-world diabetes diagnosis.

f) Model Generation

This module focuses on building and training different ML and DL models, including ANN, SVM, DT, and an Ensemble Learning Algorithm. Each diabetes prediction model is trained and evaluated using recall, accuracy, precision, and F1-score to discover the best one.

g) User Signup & Login

A secure authentication system is integrated into the platform, allowing users to register and log in. This module ensures data privacy and personalized access to diabetes monitoring. A Flask-based framework is used to implement a user-friendly interface for managing user accounts securely.

h) User Input

Users can enter their real-time health data, such as glucose levels, heart rate, and dietary habits, into the system. This module processes user inputs and prepares them for analysis, enabling personalized diabetes predictions and recommendations based on individual health parameters.

i) Prediction

The final prediction is displayed to the user based on the trained model's analysis. The system provides insights into diabetes risk levels, personalized treatment suggestions, and preventive measures. By using an ensemble method, the system enhances accuracy and reliability in diabetes detection, ensuring better health management.

iv) Algorithms:

1. ANN (Artificial Neural Network):

Through the use of interconnected layers of nodes, ANNs are able to simulate the way the brain processes data. In order to gather intricate patterns of diabetes data, this study employs ANN. ANN learns from the dataset and uses patient attributes to predict diabetes. It is an excellent option for enhancing system diabetes forecasts due to its ability to recognise complicated relationships and patterns.

```
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")
```

2. SVM

SVM does both classification and regression. SVM determines the optimal hyperplane for data point classification. Optimal distance between data points of different classes is maximised by selecting the hyperplane with the highest margin. By capturing complex dataset relationships, this project correctly detects diabetic conditions, making it a good fit using SVM. Its capacity for binary categorisation and high-dimensional space lend credence to the project's aim of precise 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")
```

3. DECISION TREE

Machine learning algorithms known as decision trees use a hierarchical representation of decisions and their outcomes to form conclusions. Core nodes reflect feature-based decisions and leaf nodes indicate outcomes in a tree structure that is created by recursively splitting the dataset into subgroups based on the most relevant attributes. An interpretable diabetes prediction model that aids in patient categorisation based on physiological factors has been developed in this study using the Decision Tree algorithm. Because of its openness, the system may be utilised to examine the parameters for diabetes diagnosis 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")
```

4. ENSEMBLE

To increase precision and robustness, machine learning ensembles pool algorithm predictions. The Ensemble Algorithm is employed in this study to improve the accuracy of diabetes prediction by combining the results of Decision Tree, SVM, and ANN. With the help of ensemble, the system is made stronger, biases are reduced, and diabetes predictions are improved, resulting in a more comprehensive and effective 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 proposed 5G-Smart Diabetes system was evaluated using multiple diabetes datasets, including the Pima Indian Diabetes dataset and other clinical datasets, to ensure robustness and generalization. Data preprocessing techniques such as handling missing values, normalization, and feature selection using the Extra Tree Classifier were applied to improve model performance. The dataset was divided into training and testing sets (80:20 ratio) to validate the models. Machine learning algorithms such as Artificial Neural Network (ANN), Support Vector Machine (SVM), and Decision Tree (DT) were trained and tested using standard evaluation metrics like accuracy, precision, recall, and F1-score. Experimental results showed that ANN achieved high accuracy in capturing complex patterns, while SVM provided strong classification boundaries and Decision Tree offered interpretability. The Ensemble model, combining all three algorithms, outperformed individual models by improving prediction accuracy and reducing errors. The results demonstrate that the proposed system provides reliable and efficient diabetes prediction, making it suitable for real-time healthcare applications.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

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

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

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

$$\Pr e cision = \frac{TP}{(TP + FP)}$$

Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

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

mAP: Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).

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

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

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

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

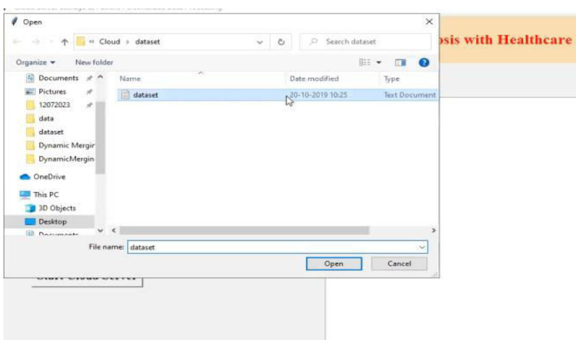

Fig2 upload dataset

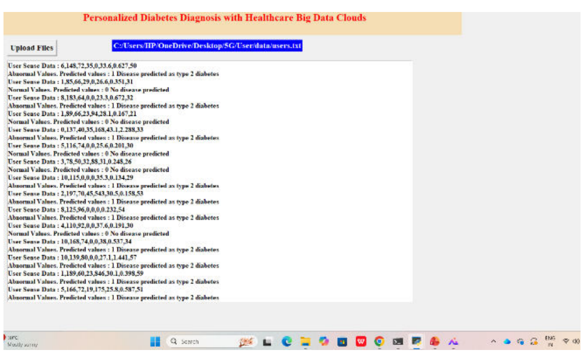

Fig3 predicted results

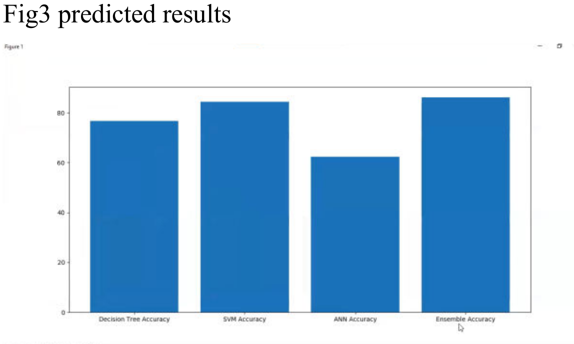

Fig4 accuracy compare graph

5. CONCLUSION

By combining wearable 2.0 technology, 5G connectivity, cloud computing, and deep learning models like CNN+LSTM, the 5G-Smart Diabetes system offers an advanced, real-time, and personalized solution for diabetes monitoring. This innovative approach not only improves early detection but also promotes proactive healthcare management, lowering hospitalizations and improving patient outcomes. Additionally, a Flask-based frontend enables seamless user interaction and secure authentication.

6. FUTURE SCOPE

The 5G-Smart Diabetes system has great promise for future developments in individualized treatment. Blockchain technology integration might increase patient privacy and data security in the future. The accuracy of diabetes detection can also be increased by integrating real-time IoT-based continuous glucose monitoring (CGM) sensors. To improve prediction performance while maintaining data privacy, advanced deep learning methods including transformer-based models and federated learning can be investigated. Additionally, adding voice-activated AI assistants and tailored food and lifestyle suggestions based on real-time data can boost user engagement. A full AI-powered healthcare solution may be created by expanding the system to track more chronic illnesses.

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