

A Home-based Diabetes Prediction System on Internet of Things, Federated Learning and Edge Computing

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Abstract. Early-stage detection of a disease is a very important step to minimize the severity of the illness. Many applications using machine learning in health-metrics tracking and prediction have gained public interests in recent years. Our research developed a health monitoring and prediction system for diabetes. In our proposed system, K-Nearest Neighbor (KNN) algorithm was executed in distribution manner using Federated Learning. It allows individuals to continuously keep track of their key health indicators without going to the hospital. Our proposed system can predict the levels of risk of diabetes and help users take preventative measures in advance. By using Federated Learning, it ensures model being trained on distributed data sources in order to preserve privacy and improve inferred accuracy. By running K-Nearest Neighbor in Federated cluster, it showed that we could gained up to 10% of predictive accuracy in comparison with the standalone version of KNN.

Keywords: Home-based health system · Internet of Things · Federated learning · Edge computing, · Diabetes prediction.

1 Introduction

Diabetes, a chronic medical condition affecting millions worldwide, necessitates innovative solutions for effective management. A Home-based Diabetes Prediction system has emerged as a groundbreaking technological advancement. Utilizing cutting-edge technologies like the Internet of Things (IoT), Federated Learning, and Edge Computing, this system aims to transform diabetes management by offering predictive capabilities and healthcare services within the confines of patients' homes.

One approach to tackle the challenge of diabetes management is through predictive analytic powered by KNN algorithms. By integrating data from diverse sources such as wearable devices, glucose monitors, and health applications. The system can analyze this information to predict the risk of diabetes. Model KNN,

trained on this extensive and a variety of datasets, can identify patterns and trends, enabling early detection and prevention.

Federated Learning ensures privacy by training models across decentralized devices, keeping patient data local. Through collaborative learning, it preserves individual privacy, enhancing data security and user confidence. This approach enables personalized care plans, analyzing historical and real-time data for customized recommendations. Remote monitoring empowers healthcare professionals to intervene promptly, enhancing care quality and encouraging patient involvement in their health management journey.

Overview, the Home-based Diabetes Prediction system represents a paradigm shift in diabetes management. Through the integration of predictive analytics, Federated Learning, and Edge Computing, it not only predicts diabetes risk but also ensures data privacy, real-time processing, and personalized care. By empowering individuals to proactively manage their health and facilitating timely interventions, this innovative system holds immense potential in the battle against diabetes and other chronic diseases. Its multifaceted approach heralds a new era of patient-centric healthcare, promising improved outcomes and a higher quality of life for individuals affected by diabetes.

Our main contributions are summarized as follows:

- Design and deploy an health monitoring system on Libelium hardware;
- Develop federated learning for prediction diabetes function;
- Build the Kubernetes cluster to save users data as so as federated learning models;
- Develop the user interfaces for two user groups: patients and medical facilities.

The rest of this paper is constructed as follows: Section 2 highlights the previous works on IoT-based and machine learning-based monitoring systems; The gap in e-healthcare and our motivation are also described at this section; Our proposal is showed at Section 3, it includes system architecture and work flows; The test-cases and performance evaluation are introduced at Section 4; The paper ends with our conclusions and future works.

2 Related Works

2.1 Remote Health Monitoring Systems

With the robust development of IoT and artificial intelligence has paved the way for transformative advancements across various domains, including healthcare. As the population increases rapidly, smart cities are recognizing the necessity of implementing home health monitoring systems [1]. The effectiveness of such systems is particularly evident during the COVID-19 pandemic when widespread lock downs were imposed [2]. Alongside the rapid progress in medical sensor technology [3], the establishment of home health monitoring systems has become even more convenient, emphasizing their importance in modern smart cities.

2.2 Diabetes Prediction using Machine Learning

Machine Learning (ML) is becoming increasingly popular in the field of healthcare and is expected to be an effective tool in preventive at-home healthcare[4]. In the medical field, the application of machine learning techniques to predict diabetes based on health data has shown significant potential. Particularly, using model KNN to detect diabetic retinopathy from retinal images is an emerging and promising area[5]. The K-Nearest Neighbors (KNN) model is one of the essential tools in machine learning with numerous advantages such as low computational cost, high durability, generalization capabilities, high performance, simplicity, and ease of understanding. Employing KNN for classifying retinal images can assist in diabetes diagnosis and monitoring disease progression effectively[6]. This demonstrates the considerable potential of KNN in enhancing healthcare quality and preventing diabetes.

2.3 Federated Learning for Privacy-Preserving Healthcare

Federated learning, as highlighted in the reference [8], has become a pivotal solution for mitigating privacy concerns in healthcare data sharing, a critical issue discussed in [7]. This innovative approach revolutionizes the landscape of data-driven healthcare by enabling model training across a multitude of decentralized data sources without necessitating the sharing of raw, sensitive patient information.

One notable contribution to the field comes from Li et al., detailed in their comprehensive work [9]. They introduced a sophisticated federated learning framework meticulously designed for disease prediction, drawing upon electronic health records (EHRs) [10] sourced from diverse hospitals. What sets this framework apart is its ability to empower model KNN to collaboratively learn and improve prediction accuracy without compromising individual data privacy.

2.4 Gap and Motivation

Existing research has delved into remote health monitoring, diabetes prediction using KNN, and federated learning in healthcare separately. However, there is a lack of integration in these areas. Our study fills this gap by creating a remote health monitoring platform that predicts diabetes with KNN. We enhance predictive accuracy and preserve user data privacy through federated learning. By combining these techniques, our system provides precise health insights and personalized predictions, addressing privacy concerns related to sensitive health data.

3 System Design

3.1 Architecture of the Health Monitoring System

The design of our health monitoring system follows a modular architecture Edge Computing that consists of three main components: the cloud layer, the edge layer, the device layer.

The Cloud Layer is the topmost tier in our health monitoring system, managing data from the edge and device layers. It serves as a centralized hub for data storage, analytics, and user interfaces. Historical health data is stored for long-term analysis, using advanced algorithms like KNN for insights and predictions. User interfaces, such as web-based dashboards and mobile apps, enable users and healthcare professionals to access information and make informed decisions. Strong security measures protect sensitive health data during transmission and storage.

The Edge Layer acts as a mediator between the cloud and device layers, pre-processing and filtering data before sending it to the cloud. This reduces latency and enhances real-time monitoring. Raw data is cleaned, filtered, and aggregated here, minimizing the data sent to the cloud. Basic analysis and anomaly detection enable swift responses to health events. Edge devices, like gateways or servers, are strategically placed to manage data flow efficiently.

The Device Layer is crucial in our health monitoring system, housing devices like fitness trackers, medical sensors, and IoT devices. These gadgets collect real-time health data such as heart rate, blood pressure, temperature, and activity levels. The gathered data is sent securely to the edge layer for preprocessing and then to the cloud layer for storage and analysis. To ensure uninterrupted monitoring, these devices are designed with energy-efficient technologies, extending their battery life. Additionally, a variety of sensors and technologies are integrated into these devices to monitor diverse health parameters.

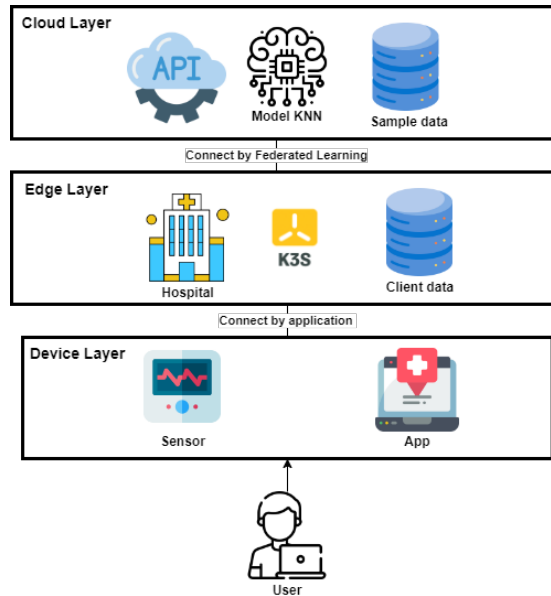


Fig. 1. Architecture of System.

3.2 User Interface and Experience

Our system's user interface prioritizes simplicity, usability, and clear data visualization. Accessible via mobile app or web portal, it displays real-time health metrics, historical trends, and personalized recommendations. Interactive visualizations and intuitive navigation enhance the user experience. Users can customize charts, graphs, and alerts and receive notifications for critical health events, like sudden glucose level changes.

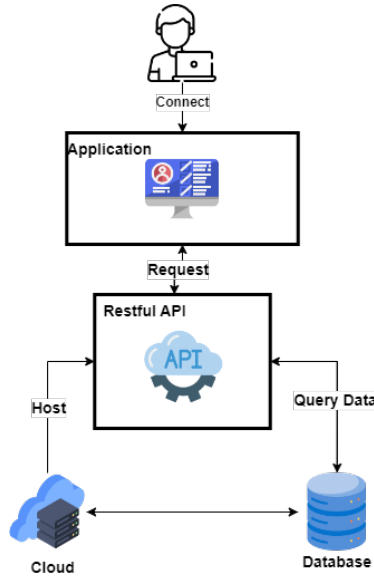


Fig. 2. Application diagram.

The user interface provides a comprehensive view of the individual's health journey. Upon logging in, users are greeted with a personalized dashboard that prominently showcases their name, creating a sense of familiarity and tailored experience. Alongside the user's name, vital health metrics are prominently displayed, offering real-time insights into their overall well-being. These metrics may include data points such as heart rate, blood pressure, glucose levels, activity levels, and more, depending on the monitoring parameters set within the system.

In addition to the immediate health metrics, the interface offers a dedicated feature for diabetes monitoring. A prominent and easily accessible button labeled "Diabetes Diagnosis" is present, allowing users to initiate a diabetes assessment. Upon clicking this button, the system may prompt users to input specific health data relevant to diabetes diagnosis, such as fasting blood sugar levels or other pertinent information.

The user interface is designed with a focus on user-friendliness and efficiency. The diabetes diagnosis button serves as a proactive tool, empowering users to assess their diabetes risk conveniently. This intuitive design encourages regular health check-ins, fostering a proactive approach to health management. Overall, the interface not only provides essential health data at a glance but also facilitates active engagement and health-conscious decision-making through its user-friendly features.



Fig. 3. User interface.

3.3 Architecture of Federated Learning

We'll start by using existing data to craft our training weights, employing the powerful K-Nearest Neighbors (KNN) algorithm and GridSearchCV. This process occurs on a cloud-based platform, ensuring scalability and computational efficiency.

As we venture further into the process, the heart of our system will revolve around the implementation of Federated Learning (FL), facilitated by the seamless communication capabilities of sockets. These sockets will serve as the conduits through which data flows securely and efficiently, enabling the transfer

of knowledge between our centralized cloud platform and a network of diverse healthcare institutions.

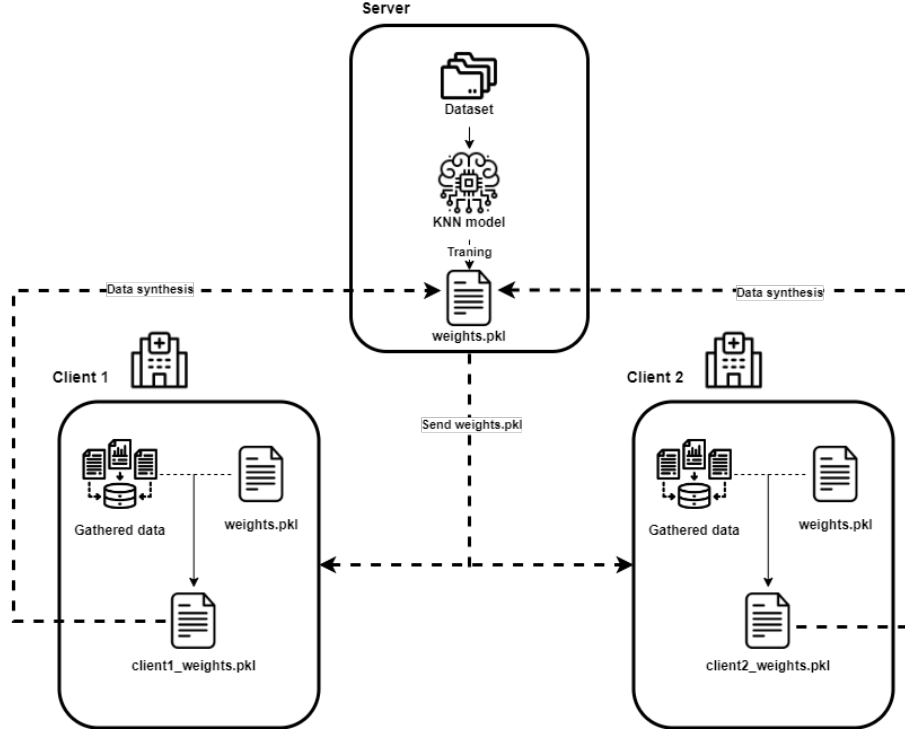


Fig. 4. Federated Learning.

Within every healthcare facility, a crucial transformation takes place, driven by cutting-edge technology and collaborative efforts. The process begins with the reception of training weights sourced from the cloud through secure socket connections. These weights play a pivotal role, guiding the local training process within the confines of each hospital.

During this localized training phase, the model undergoes refinement, honing its parameters using the institution's specific and unique dataset. This intricate process ensures that the model becomes intimately acquainted with the intricacies of the data it is meant to analyze. Through continuous iterations, the model updates its training weights, enhancing its accuracy and relevance.

After local training, refined weights with insights from healthcare institutions are securely transmitted to the cloud. There, diverse data undergoes harmonization, akin to orchestrating a symphony. Each institution's data contributes to a unified model, embodying collective knowledge and expertise. This collaborative effort showcases the power of shared wisdom from medical entities.

With aggregated training weights, our model makes accurate, nuanced predictions, informed by diverse medical data. This holistic approach integrates cloud computing, federated learning, and medical expertise, marking a new era in healthcare solutions. Facilitated by socket connections, it enables seamless communication, paving the way for data-driven, collective intelligence in healthcare decisions, enhancing patient care and outcomes.

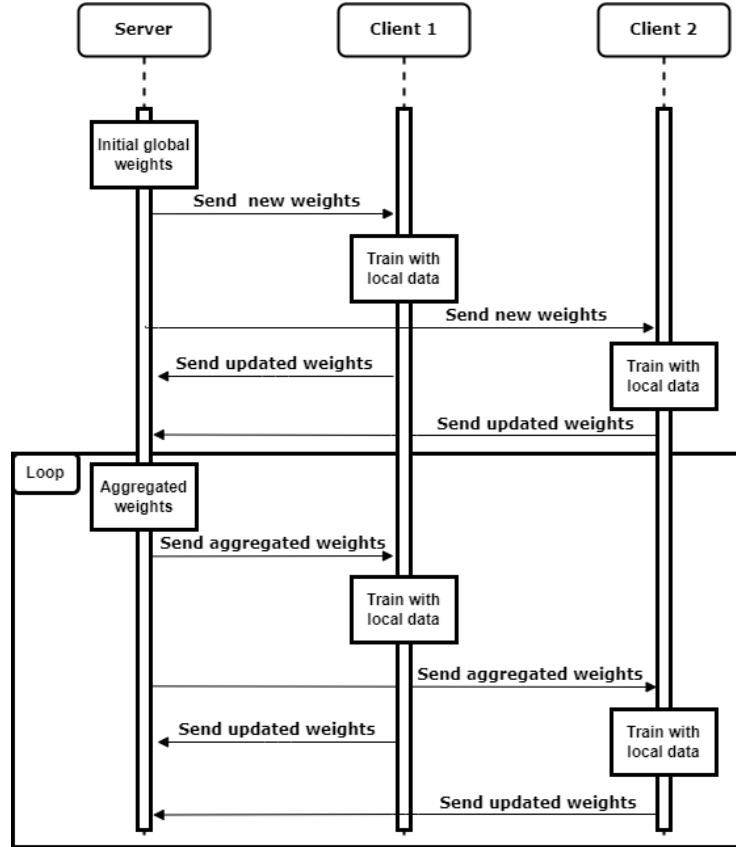


Fig. 5. Sequence diagram of Federated Learning.

3.4 Cluster K3S

K3S Clusters, powered by Raspberry Pi devices, mimic hospitals. MySQL within these clusters acts as a secure data repository, serving both as a database and a client for our Federated Learning model, enhancing data security and model capabilities. This synergy showcases our sophisticated healthcare solution.

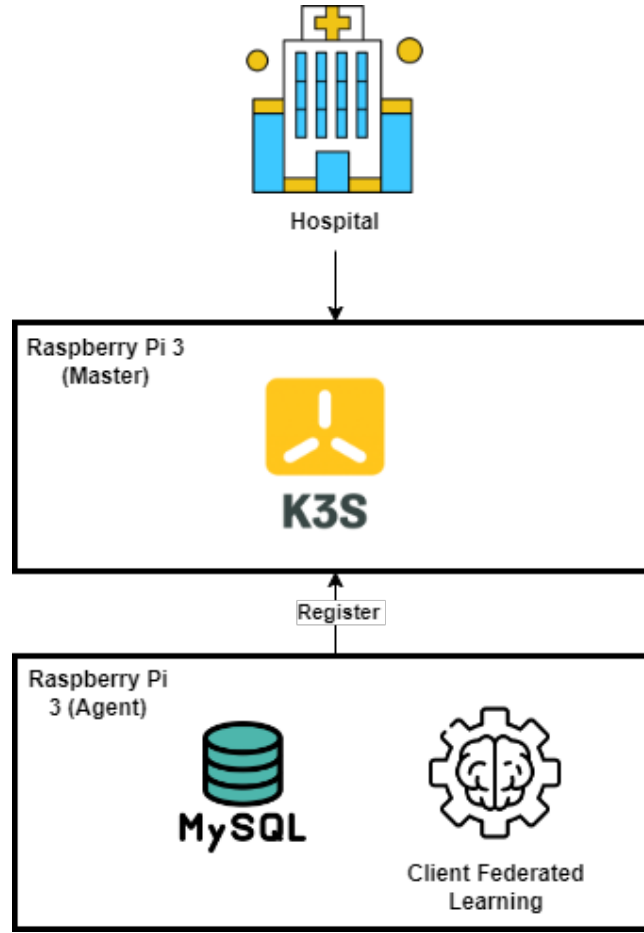


Fig. 6. Cluster K3S.

4 Performance Evaluation

4.1 Evaluation of Training Data

The dataset used for training in our study is the Pima Indian Diabetes (PID) dataset [11]. The dataset we are working with is fundamental to our diabetes prediction model, providing a rich source of information in CSV format. It consists of 768 rows and encompasses 9 essential columns, each capturing specific health parameters vital for our analysis.

Firstly, the 'Pregnancies' column documents the number of pregnancies each individual has undergone, offering valuable insights into their reproductive history. 'Glucose' stands for the fasting blood sugar levels, measured in milligrams per deciliter (mg/dL), providing critical information about glucose metabolism.

The 'BloodPressure' column records diastolic blood pressure in millimeters of mercury (mm Hg), a key indicator of cardiovascular health.

Additionally, 'SkinThickness' measures the thickness of a skinfold at the triceps in millimeters (mm), offering data related to body composition. 'Insulin' signifies serum insulin levels, presented in micro-units per milliliter ($\mu\text{U}/\text{ml}$), providing insights into insulin production and regulation. 'BMI' or Body Mass Index, a derived numerical value, characterizes an individual's overall body composition, aiding in the assessment of weight-related health risks.

The 'DiabetesPedigreeFunction' column quantifies the genetic influence of diabetes based on family history, shedding light on hereditary factors. 'Age' represents the individual's age in years, a critical factor in diabetes risk assessment. Finally, the 'Outcome' column serves as a binary variable, taking the value '1' to indicate the presence of diabetes and '0' to signify its absence.

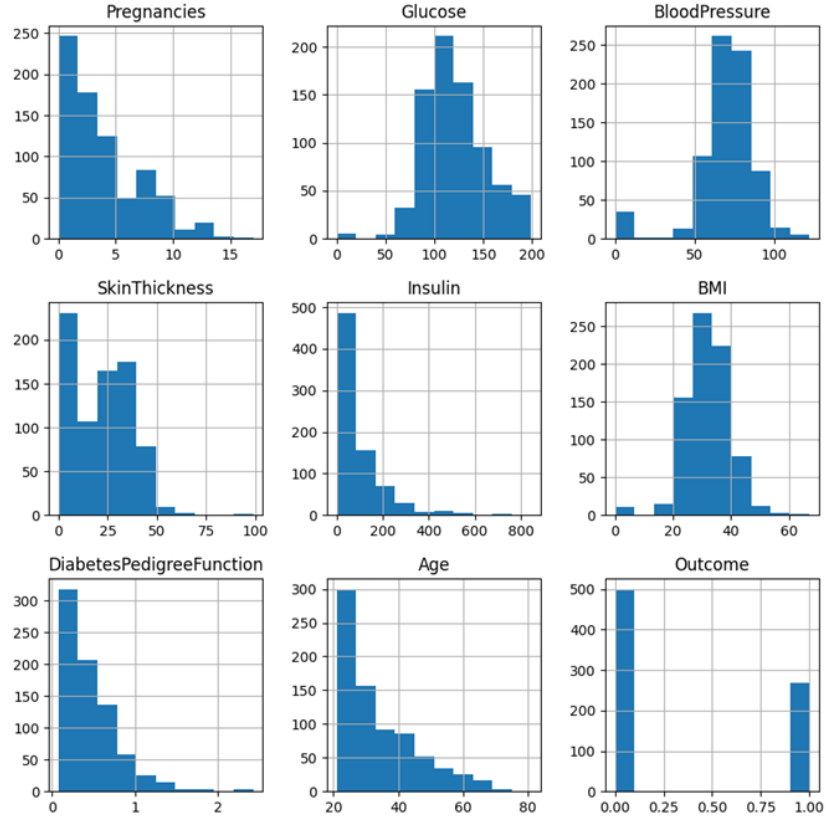


Fig. 7. Charts Representing Features.

Feature	Meaning
Count	the number of NoN-empty rows in a feature.
Mean	mean value of that feature.
Std	Standard Deviation Value of that feature.
Min	minimum value of that feature.
Max	maximum value of that feature.
25%, 50%, and 75%	are the percentile/quartile of each features.

Table 1. Description Distributed Data Statistics

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768	768	768	768	768	768	768	768	768
mean	3.84	120.89	69.1	20.53	79.79	31.99	0.47	33.24	0.34
std	3.36	31.97	19.35	15.95	115.24	7.88	0.33	11.76	0.47
min	0	0	0	0	0	0	0.078	21	0
25%	1	99	62	0	0	27.3	0.24	24	0
50%	3	117	72	23	30.5	32	0.37	29	0
75%	6	140.25	80	32	127.25	36.6	0.62	41	1
max	17	199	122	99	846	67.1	2.42	81	1

Fig. 8. Distributed data statistics table.

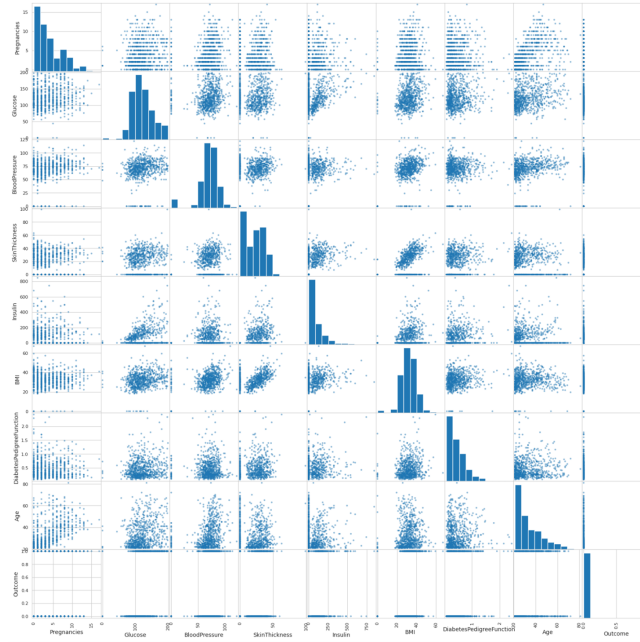
In our dataset analysis, a notable pattern emerged: as the number of pregnancies increased, insulin levels in women tended to decrease. This hints at a potential inverse correlation between pregnancies and insulin levels, especially in women. While promising, further detailed analysis and statistical confirmation are needed to validate this relationship's strength. If substantiated, this insight could significantly enhance our diabetes understanding, potentially leading to more accurate prediction models and focused prevention strategies. These preliminary findings inspire further research, driving us to explore deeper patterns and relationships, advancing our knowledge in diabetes prediction.

This finding is particularly crucial as it could have far-reaching implications for understanding the risk factors associated with diabetes. However, it's essential to note that further in-depth research and rigorous statistical analysis are necessary to confirm the strength and significance of this relationship. Despite the need for additional investigation, these initial observations serve as valuable and promising starting points for our ongoing exploration of patterns within the dataset.

Understanding such relationships can profoundly impact our ability to predict and prevent diabetes effectively. These preliminary insights provide a strong foundation for our future studies, guiding our focus as we delve deeper into the intricacies of the data, aiming to uncover more nuanced patterns and correlations for a comprehensive understanding of diabetes risk factors.

4.2 Evaluation of predictive models

In our environment, the server runs Ubuntu 22.04 on the OpenStack platform, while two Ubuntu 20.04 virtual machines on VMware 17 Pro serve as clients. The

**Fig. 9.** Scatter Matrix

Pima Indian Diabetes (PIDD) dataset is divided into parts, with 60% residing on the server and 20% on each client. For aggregation, model weights are calculated as the average of weight files sent by each client to the server.

Table 2. Performance Evaluation

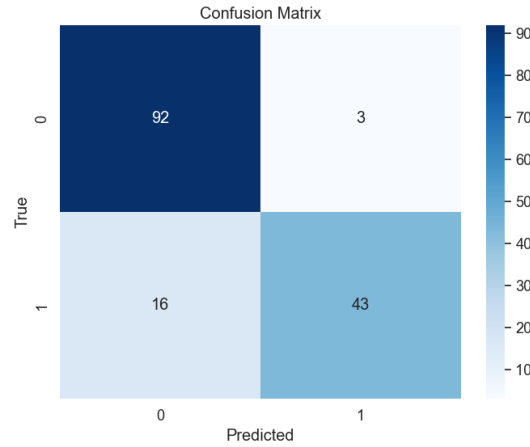
Resources	Server	Client 1	Client 2
CPU (%)	57	31	30
RAM (MB)	1365	1090	1080

In terms of evaluation results, the original K-Nearest Neighbors (KNN) algorithm achieved an accuracy of 79%. However, after implementing Federated Learning (FL), the model's performance significantly improved to an accuracy of 87%.

Table 3. Evaluation results of traditional KNN model and our proposal

Metric	KNN	KNN + FL	Description
Accuracy	0.79	0.87	Measures overall correctness
Precision	0.70	0.86	Gauges accurate positive predictions
Recall	0.63	0.81	Captures actual positive instances well
F1-Score	0.66	0.84	Balances precision and recall

These results suggest that FL has substantially enhanced the model’s predictive capabilities in the described setting, making it a promising approach for improving diabetes prediction. Nonetheless, continuous refinement may be necessary to ensure that the model consistently achieves high accuracy while minimizing the risk of missing diabetes cases.

**Fig. 10.** Confusion Matrix.

5 Conclusion and Future Works

In this paper, we develop a solution for e-healthcare via a variety of technologies, such as Internet of Things, Federated learning, and Edge Computing. While IoTs and Edge Computing ensure the connectivity of users, devices, and services, Federated learning supports Deep Learning on learning users data without collecting all of them. The results show that our proposal outperform the centralized learning in deep learning evaluation metrics while keeping users data security and privacy.

The system offers several promising avenues for development. Firstly, it can expand its predictive capabilities beyond diabetes, encompassing other health-

related conditions such as cardiovascular diseases and type 2 diabetes. This expansion provides users with a more comprehensive view of their health. Secondly, ensuring the privacy and security of medical data is paramount, necessitating ongoing research into data protection measures, including data encryption and privacy management. Lastly, creating user-friendly mobile applications and interfaces is vital for enhancing user engagement and making it easy for individuals to track and manage their health information on-the-go.

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