Online-Journals.org

iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 21 No. 14 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v21i14.58035

PAPER

Towards Smart Healthcare Teleconsultation: A Secure IoT-Edge-Machine Learning Architecture for Diabetes Data Collection and Prediction

Dior Masrane Reoukadji[1] (✉), **Olivier Mekila Mbayam**[2], **Imam Alihamidi**[1,3], **Patrick Loola Bokonda**[4], **Abdessalam Ait Madi**[1]

[1]Laboratory of Advanced Systems Engineering, Ibn Tofail University, Kenitra, Morocco

[2]Euromed University, Fes, Morocco

[3]Moroccan School of Engineering Sciences (EMSI Rabat/SMARTILAB), Rabat, Morocco

[4]Haute Ecole de Commerce de Kinshasa (HEC-Kin), Kinshasa, Democratic Republic of Congo

dior.masranereoukadji@uit.ac.ma

ABSTRACT

The increasing demand for medical consultations in developing countries is one of the largest pressures on healthcare systems. In this study, an IoT-enabled device was proposed for automating the collection of physiological data for diabetes classification and prediction. The collected data was stored on ThingsBoard Cloud for convenience in teleconsultations and reduction of physical visits. The system use edge computing (EC) technology implemented through a Raspberry Pi server and makes use of the ThingsBoard cloud for data monitoring and visualization. However, for data confidentiality, integrity, and secure access, the system includes user authorization, data encryption, and secure transmission mechanisms. Furthermore, machine learning (ML) models based on random forest (RF) and XGBoost were used for predicting diabetes from the collected data. Precision, recall, F1-score, and accuracy analysis revealed that RF performs better than XGBoost, achieving 99% overall accuracy with commendable efficiency on all the above metrics. Therefore, future research work should include increasing system security with better threat detection mechanisms, improving ML models by using hybrid mechanisms, and anonymizing data for compliance with data privacy frameworks for health data to realize smarter, more secure, and more accessible healthcare delivery.

KEYWORDS

edge computing, data collection, smart healthcare, teleconsultation, IoT technology, machine learning in healthcare, diabetes predictions, sustainable development

1 INTRODUCTION

Diabetes diagnosis continues to be a major challenge in healthcare, driven by the increasing global prevalence and serious health consequences. The World Health Organization (WHO) reports that diabetes cases have skyrocketed from 108 million to 422 million between earlier years and 2014, with an estimation to reach 629 million

Reoukadji, D. M., Mbayam, O. M., Alihamidi, I., Bokonda, P. L., Madi, A. A. (2025). Towards Smart Healthcare Teleconsultation: A Secure IoT-Edge-Machine Learning Architecture for Diabetes Data Collection and Prediction. *International Journal of Online and Biomedical Engineering (iJOE)*, 21(14), pp. 76–96. https://doi.org/10.3991/ijoe.v21i14.58035

Article submitted 2025-08-11. Revision uploaded 2025-09-27. Final acceptance 2025-09-27.

by 2045 [1], [2]. In 2016, research shows that diabetes was responsible for around 1.6 million deaths globally [3]. Therefore to prevent, early detection, it is crucial to avoid kidney disease, stroke, vision loss, cardiovascular events, and limb amputations [4]. There are different types of diabetes, such as Type 1, Type 2, and gestational diabetes. Type 1 diabetes happens when the pancreas doesn't make enough insulin. In contrast, Type 2 diabetes happens when the body can't use insulin properly [5]. Additionally, gestational diabetes happens during pregnancy and causes high blood sugar levels in pregnant women [6]. In the literature, there are several ways of managing diabetes, such as checking blood sugar levels, frequently done with finger-prick tests but these technologies struggle with data collection [7], [8]. To address it, new technology such as Continuous Glucose Monitoring (CGM) systems is changing the way diabetes is treated by giving real-time information and making less use of intrusive treatments [9].

Recently, researchers are increasingly using artificial intelligence (AI) and Internet of Things (IoT) technologies in healthcare for disease prediction and management [7], [10]. These technologies hold huge potential due to their processing abilities of vast volumes of data, uncovering complex patterns, and making predictive analyses more accurate. Additionally, Edge Computing (EC) and Cloud Computing (CC) contribute to reshaping healthcare delivery and real-time emergency management systems [11]. EC will contribute to improving smart healthcare systems and CC infrastructure to optimize data processing and rapid decision-making, such as delays, data packet loss, and transmission inaccuracies that lead to misdiagnoses and treatment errors, particularly during emergencies. In addition, the integration of EC with ML techniques holds significant promise for enhancing patient-centered outcomes. This study focuses on ML applications within healthcare systems. This work is organized as follows: Section 2 highlights related works and their limitations, Section 3 discusses the proposed methodology, Section 4 discusses different obtained results, and Section 5 concludes this study.

2 RELATED WORKS

In the last decades, research in the healthcare systems based on IoT, EC, AI, and blockchain technologies has tremendously increased [12]. However, one key challenge is still reliability amid potentially faulty fog nodes. Therefore, J. O. Arowoogun et al. [13] have deployed a decision tree algorithm locally on edge devices to enable classification of physiological data with reduced communication overhead compared to cloud-centric approaches, achieving faster response time. Similarly, another research used dynamic priority-based task scheduling and adaptive resource allocation frameworks at the edge to improve throughput and decrease task completion on time in simulated healthcare scenarios, though real-world implementation and support for heterogeneous devices [14]. Furthermore, another research addresses security issues in using blockchain technology with fog computing to control sensitive sensor medical data [15]. Redactable blockchains with edge/cloud storage architecture also have been introduced to support privacy-preserving healthcare computation by maintaining auditability while scalability and security are still in the process of development [16]. Additionally, blockchain and fog-based decentralized identity and authentication protocols were introduced to improve security and robustness [17].

Another study used AI and IoMT (Internet of Medical Things) devices integrated with deep neural networks to improve health forecasting and surveillance for vulnerable populations [18]. These approaches suggest further exploration into adaptive resource management and EC integration to reduce cloud dependence. Also, predictive machine learning models trained on physiological data have shown promise for early detection of cardiovascular disease, with plans to expand to multi-disease prediction and real-time system integration while addressing privacy and robustness in diverse populations [21]. Also, federated learning combined with blockchain allows decentralized model training on edge and fog nodes without exposing raw data, preserving privacy and improving decision accuracy [22]. The research shows the need for lightweight federated learning algorithms and scalable blockchain solutions tailored for constrained healthcare IoT devices.

Some researchers used machine learning-based intrusion detection algorithms such as radial basis function neural networks to enhance protection by achieving high detection accuracy and low false positives; however, future improvements need to include unsupervised learning and real-time monitoring to detect novel threats [23]. Therefore, despite progress made in smart healthcare systems in healthcare IoT deployments, combining with platforms using low-power hardware designs alongside optimized software strategies demonstrates significant energy savings during data acquisition and transmission without degrading data quality [19], [20]. Regarding Smart Medical Gate (SMG), Reoukadji et al. [24] present the development of an IoT-based device designed to automatically collect key physiological data from patients to streamline and enhance medical consultations. However, the study is limited to the collection of physiological from patients without explicitly considering a particular disease for a remote solution in a rural area. Further, another study [25] explores voice-activated medicine to enable patients to be reminded to taking their medications but is still limited to just notifications. To fill these gaps in remote control and prediction in isolated areas in developing countries. A case of diabetes is chosen to highlight the applicability of IoT and machine learning in healthcare sectors.

3 MATERIALS AND METHODS

3.1 System architecture

The system architecture proposed in this study consist of a prototype for collecting physiological data [26] from patients in remote areas using smart hospital gate concept for diabetes monitoring and classification. Medical sensors used are MAX30100 [27] pulse oximeter (SpO_2 and heart rate), the ADS1292R [28] analog front-end electrocardiogram (ECG), the MLX90614 [29] temperature sensor, HC-SR04 [30] ultrasonic sensor, a load cell and HX711 Amplifier sensor as illustrated in Figure 1, using WeMo's R1 a development board that features the ESP8266 microcontroller [26], [31]. WeMo's R1 is responsible for acquiring raw data from sensors and transmits it to Raspberry Pi for edge preprocessing before transmission to the ThingsBoard cloud for further analysis. In this experimental system, Raspberry pi plays a pivotal role in real-time medical data processing by enabling local inference reducing latency and ensures faster decision-making. Therefore, upon receiving signals from various sensors (such as the ECG, SpO_2, heart rate, height, weight and temperature) several advanced techniques are applied to condition the raw data. For data transmission, the system is structured into different layers. The sensing layer is the starting point where data are collected from various sensors. Further, the communication between sensors and WeMo's R1 is managed via protocols such as I2C, SPI, and 1-Wire, ensuring compatibility with the different sensor types used in the system [32], [33], [34]. Moreover, once the raw data reaches the Raspberry Pi, the edge layer takes over, performing necessary data conditioning and preprocessing reducing the amount of raw data to be sent to the cloud and enables faster, more efficient processing. However, for security concern before sending data to the cloud it ensures that only authenticated devices can communicate with the system using security protocols like Open Authorization (OAuth) and JSON Web Token (JWT) [35]. This guarantees the integrity of the system by preventing unauthorized access. Afterwards, the networking layer takes charge for ensuring secure data transmission. During transmission , data is encrypted using secure protocols like MQTT [36], and firewalls [37] providing an additional layer of protection from malicious threats. At the application layer, the processed data is uploaded to the ThingsBoard cloud platform, for visualization and analysis in real-time. It allows healthcare professionals to monitor the patient's vital signs through dashboards. At this point, data security [38], is enabled using user authentication and authorization mechanisms, allowing only authorized personnel, such as doctors, to view or interact with the data. Also, DAG (Directed Acyclic Graph) or Tangle technology [39] is employed to maintain data integrity, ensuring that data cannot be interfere during transmission [40].

The ThingsBoard platform shows the results and predictions made by the machine learning models and doctors or other healthcare professionals use the graphical data and machine learning predictions to make smart choices on how to care for patients.

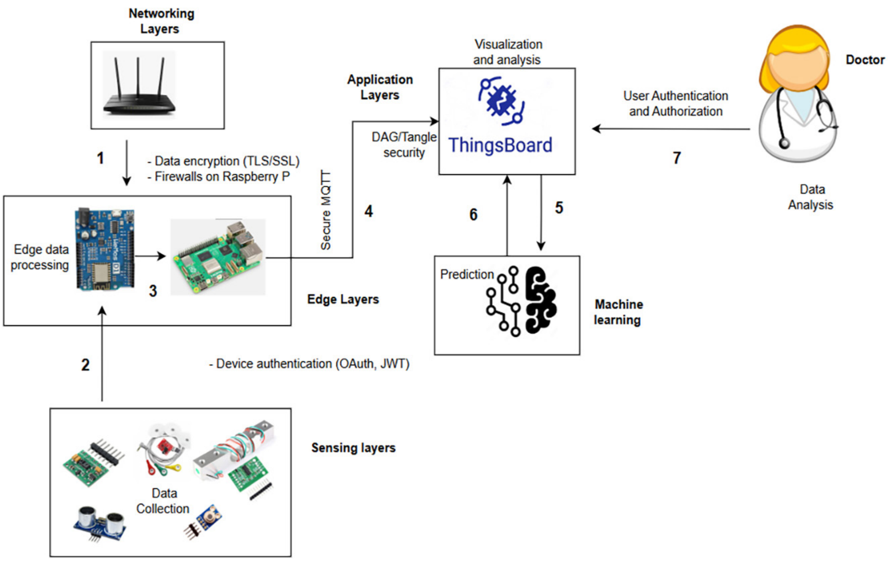


Fig. 1. Proposed system architecture

The proposed architecture uses a set of sensors such as photoplethysmography (PPG) sensor that detects changes in blood volume in the microvascular blood mostly on cardiovascular parameters including heart rate and blood oxygen saturation (SpO_2). The MAX30100 sensor sends out light from red and infrared LEDs and then detecting the light that bounces back as illustrated in the Equation (1) [41].

$$p(t) = DC + AC \cdot sin(2\pi f_{HR} t) + \eta(t) \tag{1}$$

Where:

- $p(t)$: Measured signal at time t
- DC: Baseline amount of tissue absorption showing blood flow that doesn't pulse.
- AC: Pulsatile blood volume component corresponding to the arterial pulse, which is modulated by heart rate.
- f_{HR}: Phase term, adjusting the sinusoidal wave relative to time.
- $\eta(t)$: Noise term, including motion artifacts, ambient light interference, and sensor noise.

The electrocardiogram sensor ADS1292R used waveform to monitor the electrical activity of the heart and detect arrhythmias. It includes numerous distinct phases, such as the P wave, QRS complex, and T wave, which corresponds to different stages of the cardiac cycle and is mathematically expressed as in Equation (2) [42].

$$E_{filtered}(t) = E(t) * h(t) \tag{2}$$

Where:

- $E(t)$: Original (noisy or raw) signal reflects the actual ECG signal, which includes the P, QRS, and T waves.
- $h(t)$: Impulse response of the filter represents the noise term caused by muscle action, power line interference, and other environmental influences.

Temperature measurements were obtained using the MLX90614 sensor, a non-contact infrared thermometer that combines an IR-sensitive thermopile detector and a signal conditioning ASIC (Application Specific Integrated Circuit) within a compact TO-39 package [43]. This sensor enables automated temperature data collection without the need for physical contact.

The MLX90614 sensor provides two main temperature readings:

- **Object Temperature (T_{obj}):** the temperature of the target which is the human body
- **Ambient Temperature (T_{amb}):** the surrounding temperature

The sensor measures the **infrared radiation** emitted by the object and uses the Stefan-Boltzmann law in its internal processing illustrated in Equation (3).

$$T_{obj} = \sqrt[4]{\frac{V_{IR}}{\sigma \times \varepsilon} + T_{amb}^4} \tag{3}$$

Ultrasonic sensor HC-SR04 employed in this work sense objects within its range by generating high-pitched sound waves at regular intervals. These sound waves travel through the medium of air and return to the sensor when they strike an object. For practical applications, the sensor at a constant height above the doorway has the patient standing right below. It sends out pulses at 40 kHz and waits for echoes. The time during which the signal is high corresponds to the time pass between the pulse being sent and its reception. Based on this time, the HC-SR04 sensor calculates the distance between itself and the object below it. It can detect objects within a range of 2 cm to 400 cm with an error of 3 mm. For this project, this limit has been set at 250 cm. If an object approaches within this limit, the sensor calculates the patient's height by subtracting the distance obtained from 250 cm.

The HC-SR04 calculates distance using the time it takes for the ultrasonic pulse to travel to an object and back as illustrated in Equation (4) [44].

$$Distance = \frac{v * t}{2} \tag{4}$$

- v: speed of sound in air ≈ 343 m/s = 34300 cm/s
- t: time duration between sending and receiving the pulse (in seconds)
- Division by 2 is because the time includes both **forward** and **return** travel.

In **centimeters**, and with t in **microseconds (μs)**: $Distance\ (cm) = \frac{34300 \times t}{2 \times 10^6} = \frac{t}{58.2}$.

Assuming the sensor is fixed at 250 cm above ground level, the height can be determined as illustrated in Equation (5).

$$Height_{patient} = 250 - Distance \tag{5}$$

Using Equation (4) the height will be:

$$Height_{patient} = 250 - \frac{t}{58.2} (\pm 3 \text{ mm})$$

3.2 Prototype of the architecture

The system architecture is shown in Figure 2. The primary data acquisition unit is equipped with Wi-Fi which also supports protocols such as I2C, SPI, and 1-Wire. Physiological signals are captured using the MAX30100 sensor to measure heart rate and SpO_2. For height measurement, the patient must stand under the HC-SR04 ultrasonic sensor, which is placed at a specific distance. Regarding weight measurement, the patient must stand on the electronic scale built with the Load Cell. Concerning the temperature, it is collected automatically when the MLX90614 sensor is pointed at the patient forehead. Lastly, an ECG sensor is used to collect data on the heartbeat. The system uses regulated power supplies 3.3V for sensors and 5V for the Raspberry Pi with proper wiring and decoupling capacitors to reduce electrical noise. The sensors send readings data to the Raspberry Pi, and a lightweight MQTT broker written in Python receives data and processes it through multiple stages noise filtering. Afterwards, processed data is securely uploaded to a Thingsboard IoT instance which is configured for medical monitoring. Further, the cloud platform uses API (Application Programming Interface) authentication to protect sensitive patient information while storing both raw sensor values and metadata and through an intuitive web interface. Once all the GPIO (General Purpose Input/Output) pins are initialized, you must ensure that all sensors are active. After the Pulse Oximeter is initialized, a "Success" message will appear on the serial monitor. If the initialization fails, a "Failure" message will be displayed. Also, once the device WeMo D1 Microcontroller is connected to the Internet a "success" message is displayed and the data is being sent to the Thingsboard cloud platform. To measure heart rate and SpO_2, the patient's finger will be placed on the red LED of the MAX30100.

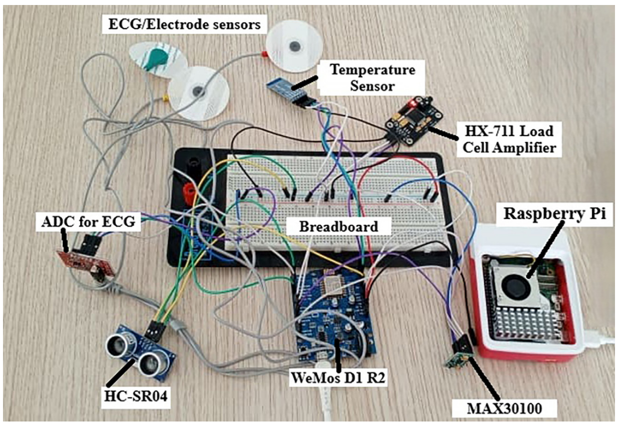


Fig. 2. Prototype of the system architecture

3.3 Pseudocode of the study

The pseudocode illustrates steps and codes used to solve the problem.

```
BEGIN SYSTEM
INITIALIZE WeMo R1 (ESP8266) with connected sensors:
   - MAX30100 (SpO2, Heart Rate)
   - ADS1292R (ECG)
   - MLX90614 (Temperature)
   - HC-SR04 (Height)
   - Load Cell + HX711 (Weight Amplifier)
CONNECT WeMo R1 to Wi-Fi network
REQUEST authentication token (OAuth → JWT)
ESTABLISH MQTT connection with Raspberry Pi (Edge Layer)
LOOP (Continuous Monitoring):
   // ---------- Sensing Layer ----------
   READ SpO2, Heart Rate from MAX30100
   READ ECG samples from ADS1292R
   READ Temperature from MLX90614
   READ Height from HC-SR04
   READ Weight from Load Cell + HX711
   TIMESTAMP = current_utc_time()
   PACKAGE RAW DATA into JSON format
   SIGN raw packet with device key
   TRANSMIT raw data via MQTT to Raspberry Pi
   // ---------- Edge Layer (Raspberry Pi) ----------
   RECEIVE raw data from device
   VALIDATE device JWT and signature
   PREPROCESS signals:
      - Filter ECG (bandpass, notch filter)
      - Extract features: HRV, R-peaks, QRS duration
      - Validate SpO2, Heart Rate, Temperature
      - Compute BMI = weight / (height^2)
   BUILD feature vector
   RUN ML MODEL (local inference) on feature vector
   OUTPUT diabetes_risk_score and classification (low/medium/high)
   IF diabetes_risk_score ≥ threshold:
      CREATE alert message
      NOTIFY local staff
      TAG alert for doctor review
   GENERATE integrity hash = SHA256(features + prediction)
   COMMIT integrity hash to DAG/Tangle network
   ADD DAG transaction ID to processed data packet
   PACKAGE preprocessed data with:
      - Features
      - ML Prediction
      - Auth JWT
      - DAG integrity info
   TRANSMIT securely to ThingsBoard Cloud via MQTT/TLS
   // ---------- Cloud Layer (ThingsBoard) ----------
   RECEIVE processed data
```

```
    VERIFY device authentication and JWT
    STORE telemetry and prediction in database
    MAP features and predictions to dashboard visualization
    IF alert received:
       TRIGGER real-time notification for doctors
       ESCALATE if unacknowledged
  // ---------- Application Layer ----------
    DOCTOR logs into ThingsBoard dashboard
    AUTHENTICATE via username/password (or 2FA)
    VIEW real-time graphs of SpO2, HR, ECG, BMI, Temp
    CHECK diabetes risk predictions
    VERIFY data integrity via DAG transaction ID
    MAKE clinical decision (e.g., adjust treatment, call patient)
END LOOP
END SYSTEM
```

3.4 Machine learning technique

In this study, a dataset from Kaggle [45] was used, since access to medical data is challenging and the setup equipment couldn't collect real data from different individuals due to privacy concerns. The data used contain patient's features such as age, BMI, glucose levels, insulin levels, and others. Before starting the analysis, the dataset is cleaned and prepared. This includes handling any missing values and converting categorical information into numerical. Once data is preprocessed, it is split into training and testing sets. Afterwards, to predict diabetes, two machine learning algorithms were applied: RF, which uses a group of decision trees, and XGBoost [46] to improve prediction accuracy. Both models are evaluated based on how well they identify whether a patient has diabetes or not, using performance indicators like accuracy, precision, and recall to determine which model performs best.

Random forest is a set of learning methods that combines multiple decision trees to form the predictive model. The final prediction is obtained by aggregating the predictions from all trees (via majority voting for classification tasks). Then, given a dataset with features $X = \{x1, x2, \ldots, xn\}$ and target y, the RF classifier constructs T decision trees $f_1(X), f_2(X), \ldots, f_T(X)$, where each tree ft(X) makes an individual prediction for class y_t. The final prediction is obtained by majority voting as illustrated in Equation (6) [47].

$$\hat{y}RF = mode(f_1(X), f_2(X), \ldots f_T(X)) \tag{6}$$

Each tree is built on a random subset of data (bootstrapped sample), and at each split, a random subset of features is considered. The model is then trained by minimizing the Gini impurity at each node of the tree, which is calculated as illustrated in equation (7) [48].

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

Where p_i represents the proportion of samples from class i in dataset D, and k is the number of classes.

XGBoost employs gradient boosting to sequentially build decision trees, where each tree aims to rectify the mistakes made by the previous one. It optimizes training by utilizing second-order derivatives (the curvature of the loss function). When applied to a dataset of N samples with features X and target variable y, Equation (8) [49] represents how XGBoost formulates the prediction for y.

$$\widehat{y}_i = \sum_{t=1}^{T} \eta f_t(x_i) \tag{8}$$

Where f_t represents the tree in the ensemble, and T is the total number of trees. It aims to minimize the loss function L, as defined in equation (9) [50].

$$L = \sum_{i=1}^{N} L\left(y_i, \widehat{y}_i\right) + \sum_{t=1}^{T} \Omega(f_t) \tag{9}$$

Where:

- $L\left(y_i, \widehat{y}_i\right)$ is the loss between true labels and predicted value.
- $\Omega(f_t)$ is a regularization term, therefore it is illustrated in Equation (10) [50].

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda \sum_{i=1}^{T} \omega_j^2 \tag{10}$$

Where γ and λ are hyperparameters controlling the complexity of the tree. The model is trained by iteratively fitting each new tree to the residuals of the previous ensemble's predictions.

The training model starts with data preparation, where the diabetes dataset (age, BMI, glucose levels, and insulin levels) is split into an 80% training set and a 20% test set, and the key hyperparameters of the RF model, including the number of trees (T), maximum depth of each tree, and number of features, are evaluated at every split. Therefore, each decision tree is trained independently on a bootstrapped subset of the data, with nodes split recursively based on the feature and threshold that either reduce Gini impurity or increase information gain. For the gradient boosting models, hyperparameters including learning rate (η) and regularization terms (γ and λ) are considered.

To assess the model's performance, k-fold cross-validation was implemented. This involves dividing our dataset into k equal portions, then repeatedly training on 80% and testing on 20% in rotation. The final performance scores are determined by averaging all metrics – accuracy, precision, recall, F1-score, and ROC-AUC – across every fold.

To evaluate the performance of the two models' RF and XGboost, different metrics were used, such as accuracy, precision, recall, and F1-score, as elaborated in Table 2.

Table 1. Performance metrics

Metrics	Formulas
Accuracy	Acc = (TP + TN)/(TP + TN + FP + FN)
Precision	Prec = TP/(TP + FP)
Recall	Rec = TP/(TP + FN)
F1-score	F1 = 2 * (Prec * Rec)/(Prec + Rec)

The interpretation of the variables for this study should be described (Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)).

With:

- TP = Person correctly identified as "having diabetes"
- TN = Person correctly identified as "non-diabetic"
- FP = Person incorrectly identified as "having diabetes"
- FN = Person incorrectly identified as "non-diabetic"

4 RESULTS AND DISCUSSIONS

4.1 Data collection and monitoring

The IoT device system's firmware was developed in the Arduino IDE using the embedded C programming language before deployment to the WeMo D1 microcontroller. The ThingsBoard dashboard receives the hospital's real-time sensor data, as illustrated in Figure 3. The system efficiently tracks and presents a range of health parameters, allowing healthcare professionals to remotely access vital patient information. Key metrics, including heart rate, oxygen saturation, weight, body temperature, and height, are processed and displayed on the dashboard in real.

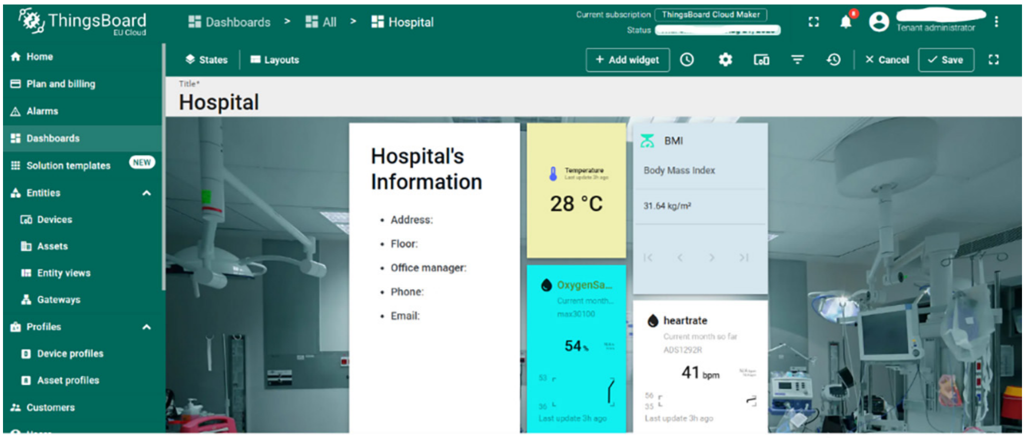


Fig. 3. Data received on Thingsboard

4.2 Prediction analysis

In Figure 4 the bar plot shows the distribution of diabetes in the dataset, with a significant imbalance between the two classes. Most individuals are non-diabetic (class 0), while a much smaller proportion is diabetic (class 1); therefore, the number of non-diabetic (Class 0) samples is significantly larger than the diabetic (Class 1) samples, the model develop a bias towards the majority class (non-diabetic), leading to poor performance when predicting the minority class (diabetic). Therefore, upsampling of the minority class (diabetic individuals) was applied by increasing the number of samples to match the majority class in order to have more balanced representation of both classes during training.

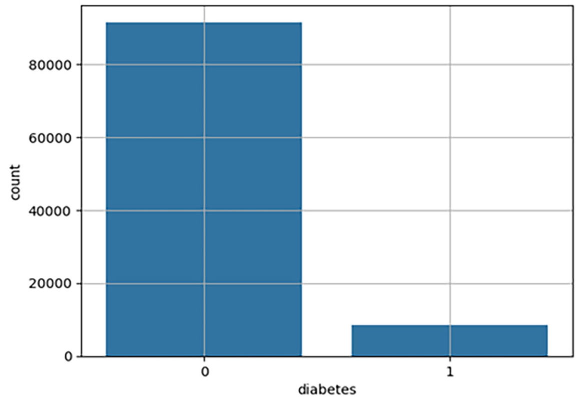


Fig. 4. Diabetes distribution

Figure 5 shows the heatmap of the correlations between features; therefore, the most notable correlations are: HbA1c_level and blood_glucose_level which have a strong positive correlation (0.42), age, and bmi, have moderate correlations with diabetes and smoking history categories are weakly correlated with diabetes. The result shows that factors such as HbA1c_level, blood_glucose_level, age, and bmi have the most influence on diabetes predictions, and it aligns with literature where HbA1c and blood glucose levels are consistently found to be highly predictive of diabetes [51].

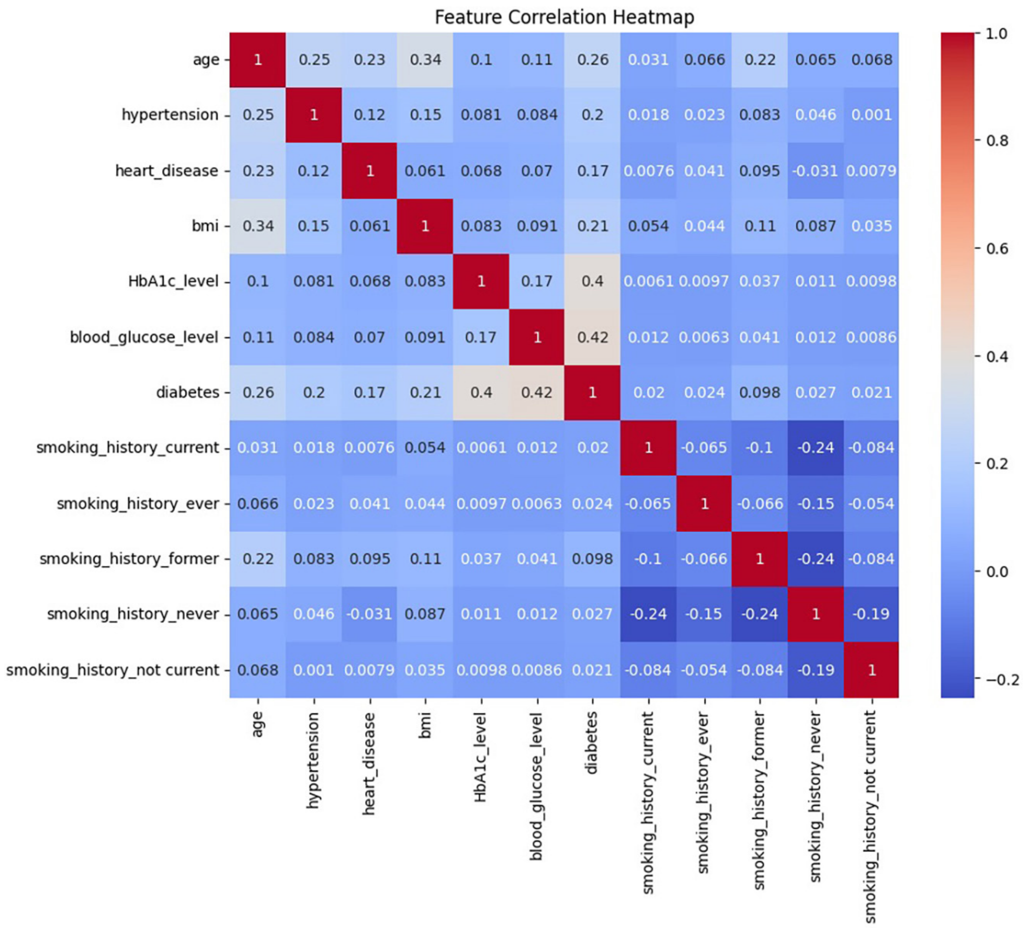


Fig. 5. Feature correlation map

As illustrated in Figure 6, the confusion matrix gives a direct comparison of actual vs predicted values for both classes. Here it shows that RF has high True Positives (TP) for both Class 0 (non-diabetic) and Class 1 (diabetic) and few False Negatives (FN) and False Positives (FP), especially for Class 1, demonstrating good performance. The results show that XGBoost has slightly more FP for Class 0 than RF, and more FN for Class 1, indicating a bit more misclassification. This result aligns with findings in the literature, where RF is often praised for its robustness to overfitting, especially as it uses an ensemble of decision trees [52]. XGBoost also has been shown to outperform many machine learning algorithms in terms of accuracy and precision, particularly in structured datasets like healthcare data [53].

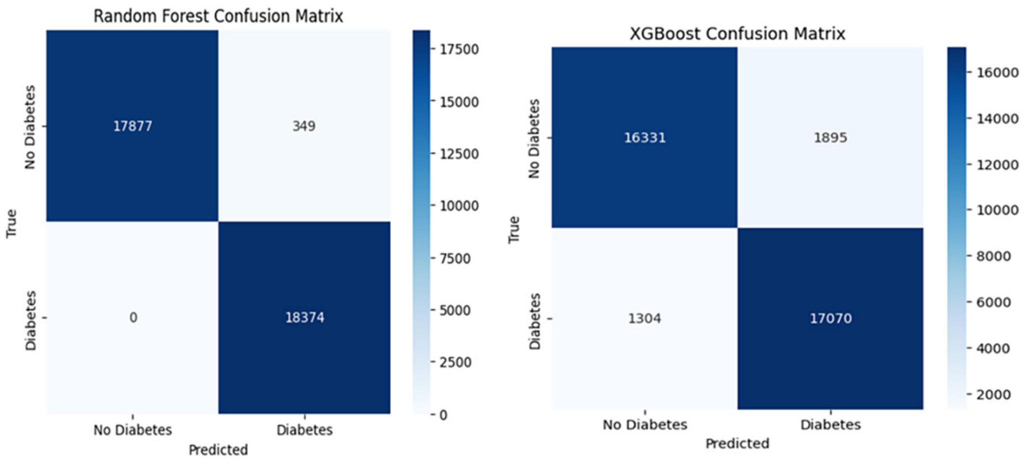


Fig. 6. RF and XGBoost confusion matrix

Figure 7 shows that both RF and XGBoost perform almost similarly in terms of precision-recall trade-offs. The high precision and sharp drop-off in recall indicate that both models tend to be conservative in predicting diabetes. RF outperformed slightly, especially in Class 1 classification, as evidenced by its superior AUC. XGBoost delivered similar performance, though its somewhat lower AUC and Precision scores suggest additional tuning could enhance results.

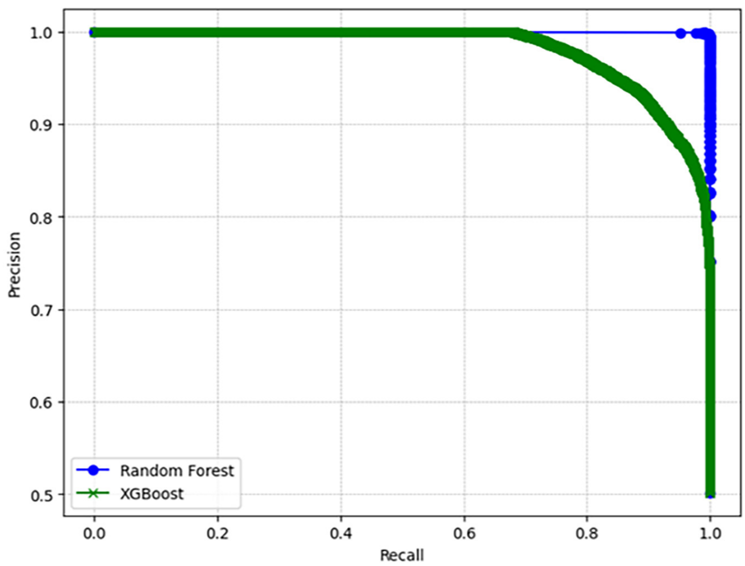


Fig. 7. Precision-recall curve for RF and XGBoost

In Figure 8, both RF and XGBoost models have ROC curves close to the ideal top-left corner, which indicates excellent classification performance. The ROC AUC score tells us about the model's ability to distinguish between the two classes (diabetic and non-diabetic) across all thresholds. The models show high similarly in AUC scores (close to 1), with nearly overlapping ROC curves – confirming their equivalent ability to distinguish diabetes cases. This aligns with the known strong performance of these algorithms for diabetes prediction [54].

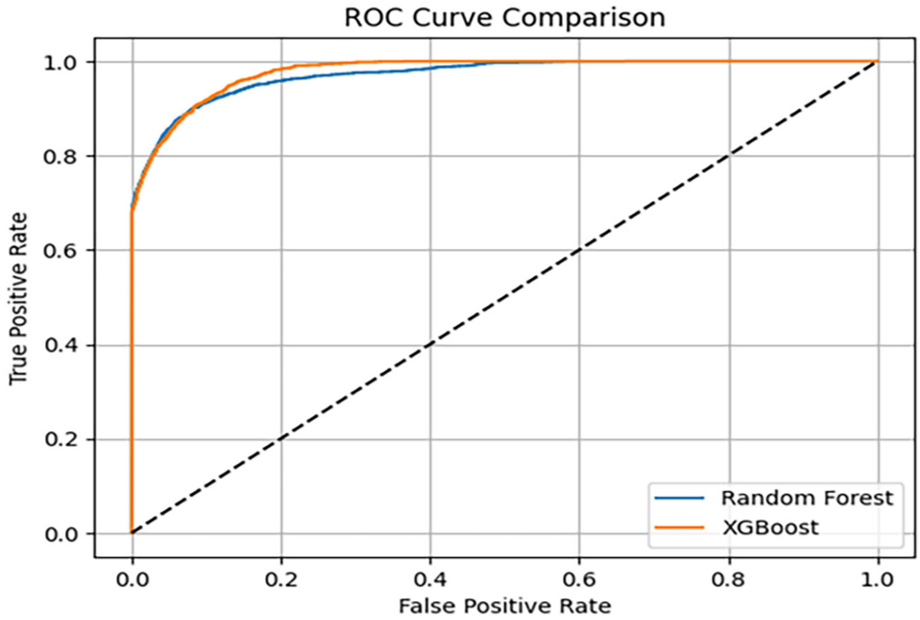
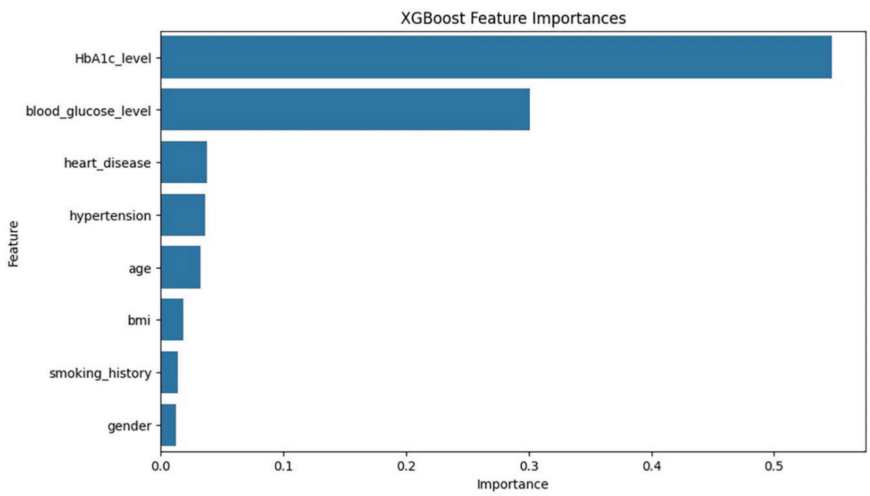


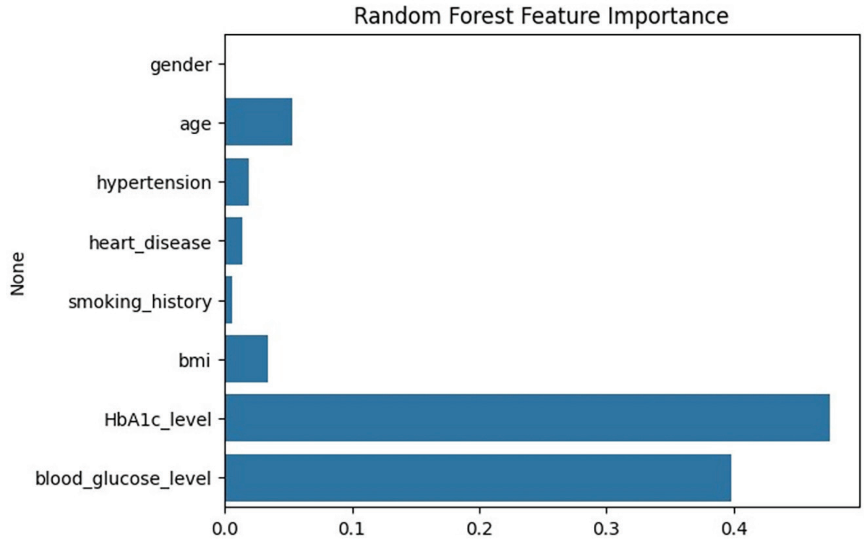
Fig. 8. ROC curve RF and XGBoost

In Figure 9, HbA1c_level and blood_glucose_level emerge as the top two most important features for diabetes prediction, far exceeding the contribution of other variables such as BMI and age. This result corroborates existing medical research [55], confirming these blood markers as primary diabetes indicators.



a) XGBoost

Fig. 9. *(Continued)*



b) Random Forest

Fig. 9. Feature importance

The SHAP value as shown in Figure 10 shows how different feature values impact the model's predictions. In this study it is observed that features such as HbA1c_level, blood_glucose_level, and bmi have the greatest effect on the model's predictions. Therefore, higher values of HbA1c_level and blood_glucose_level led to a higher likelihood of the model predicting diabetes (positive SHAP values). SHAP results confirm that blood glucose features are key diabetes predictors, with higher values directly corresponding to greater diabetic risk.

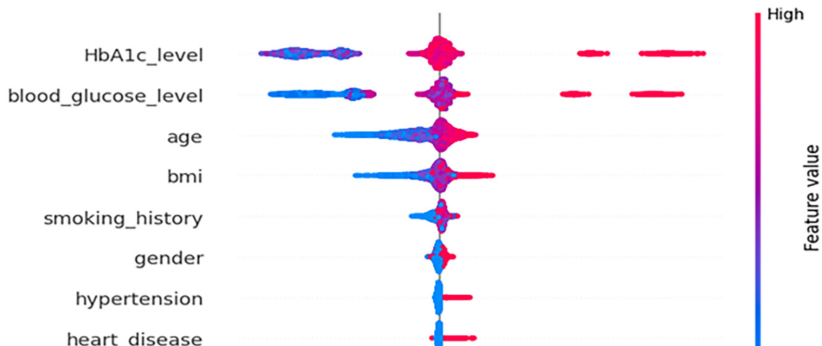


Fig. 10. SHAP value

The evaluation metrics as presented in Tables 3 and 4 shows that RF demonstrates ideal recall (1.00) for diabetic classification, correctly identifying all positive cases. Although XGBoost achieves slightly better recall (0.93) for this class, it suffers from lower precision (0.90) and substantially reduced overall accuracy (0.91 compared to 0.99). The consistent 0.99 macro/weighted averages for RF versus XGBoost's 0.91 scores verify its superior balanced classification capability. These findings support existing literature [47], [56], [57] highlighting RF's reliability with imbalanced medical datasets, while XGBoost typically requires careful tuning to manage its precision-recall tradeoffs in clinical settings where FP are problematic.

Table 2. RF model evaluation

	Precision	Recall	F1-Score	Support
0	**1.00**	**0.98**	0.99	**18226**
1	0.98	1.00	0.99	18374
Accuracy	–	–	0.99	**36600**
Macro avg	0.99	0.99	0.99	**36600**
Weighted avg	0.99	0.99	0.99	**36600**

Table 3. XGBoost model evaluation

	Precision	Recall	F1-Score	Support
0	0.93	0.90	0.91	18226
1	0.90	0.93	0.91	18374
Accuracy			0.91	36600
Macro avg	0.91	0.91	0.91	36600
Weighted avg	0.91	0.91	0.91	36600

Our study shows that XGBoost outperforms slightly RF on accuracy, precision, and shows a larger gain in ROC AUC (0.978 vs 0.964) (refer to Table 4). However, in the literature, both outcomes are common: some studies report RF slightly better on AUC or F1 [58], [59], while others report XGBoost as the top performer. Also, it is noticed that performance is strongly related to dataset and preprocessing methods.

Table 4. Comparative study

References	Random Forest	XGBoost	Performance
Our study	RF has an accuracy of 0.97065 with precision (Class1) 0.95165 and ROC AUC 0.96365	XGBoost has an accuracy of 0.97105 with precision (Class1) 0.95414 and ROC AUC 0.97819	XGBoost is slightly better on all metrics; the ROC AUC improvement is the largest.
Teja et al. [58]	RF & Bagged Trees ROC-AUC ≈ 0.95	XGBoost ROC-AUC ≈ 0.94	Both models are high-performing; RF slightly higher AUC in that study.
Imani et al. [60]	Reported accuracy/F1/AUC across imbalance/upsampling; RF performs strong, especially with upsampling.	XGBoost is competitive, but performance depends on the resampling method.	The paper emphasizes that resampling (SMOTE/ADASYN/GNUS) and imbalance levels strongly affect which model leads.
Shao et al. [61]	RF shows strong accuracy/stability across sensors (reported as top performer on some splits).	XGBoost is slightly better on some features.	Suggests feature fusion and input representation shift relative performance.
Karunakaran et al. [62]	F1 ≈ 0.93	F1 ≈ 0.92	Both ensemble methods perform very well, but RF has a marginally higher F1.
Murteza H. Tuama et al. [59]	RF ROC-AUC reported up to **0.9923** in that study.	XGBoost: high AUC is slightly lower than RF	RF outperforms XGBoost on AUC by a small margin.

5 CONCLUSION

The implementation of experimental setup using EC systems for smart health monitoring path a way to a broader adoption, particularly in remote areas with limited infrastructure. Therefore, this study used Raspberry pi to process data locally reducing latency, ensuring faster decision-making, and alleviating the need for constant cloud communication. In addition, the integration of artificial intelligence, specifically RF and XGBoost, further enhances the system's ability to analyze medical data. The results of our evaluation reveal that RF outperforms XGBoost in terms of precision, recall, and overall accuracy, particularly in identifying non-diabetic individuals and achieving flawless recall for diabetics. The study proves that edge-based AI systems, particularly those using more robust algorithms, can transform healthcare delivery in remote areas by providing accurate, instantaneous health assessments without reliance on cloud infrastructure. Despite significant progress observed during this test regarding data collection for diabetes in remote hospitals by automatizing the tasks and the strong performance of RF, it is recommendable for future research to enhance computing EC systems and machine learning models by improving model performance and addressing class imbalance using techniques such as class weighting, under sampling, or SMOTE. Also, to test both RF and XGBoost in a hybrid model. Additionally, enhancing the explain ability of models with SHAP values could also improve transparency, increasing trust and adoption in healthcare environments.

6 REFERENCES

[1] D. Lovic, A. Piperidou, I. Zografou, H. Grassos, A. Pittaras, and A. Manolis, "The growing epidemic of diabetes mellitus," *Current Vascular Pharmacology*, vol. 18, no. 2, pp. 104–109, 2020. https://doi.org/10.2174/1570161117666190405165911

[2] C. Bommer *et al.*, "Global economic burden of diabetes in adults: Projections from 2015 to 2030," *Diabetes Care*, vol. 41, no. 5, pp. 963–970, 2018. https://doi.org/10.2337/dc17-1962

[3] P. Arokiasamy, S. Salvi, and Y. Selvamani, "Global burden of diabetes mellitus," in *Handbook of Global Health*, I. Kickbusch, D. Ganten, and M. Moeti, Eds., Springer, Cham, 2021. https://doi.org/10.1007/978-3-030-05325-3_28-2

[4] F. Anwar, Qurat-Ul-Ain, M. Y. Ejaz, and A. Mosavi, "A comparative analysis on diagnosis of diabetes mellitus using different approaches – A survey," *Informatics in Medicine Unlocked*, vol. 21, p. 100482, 2020. https://doi.org/10.1016/j.imu.2020.100482

[5] M. Apostolopoulou, V. Lambadiari, M. Roden, and G. D. Dimitriadis, "Insulin resistance in Type 1 diabetes: Pathophysiological, clinical, and therapeutic relevance," *Endocrine Reviews*, vol. 46, no. 3, pp. 317–348, 2025. https://doi.org/10.1210/endrev/bnae032

[6] L. Jiang *et al.*, "A global view of hypertensive disorders and diabetes mellitus during pregnancy," *Nature Reviews Endocrinology*, vol. 18, pp. 760–775, 2022. https://doi.org/10.1038/s41574-022-00734-y [Accessed: May 19, 2025].

[7] A. K. Mishra, M. Pandey, A. Pannu, H. K. Dewangan, and P. K. Sahoo, "Review on diabetes mellitus: An insight into the current scenarios, the challenges of therapy, and application of traditional drugs," *CTM*, vol. 10, no. 3, p. e010523216399, 2024. https://doi.org/10.2174/2215083810666230501212125

[8] S. Shilo *et al.*, "Continuous glucose monitoring and intrapersonal variability in fasting glucose," *Nature Medicine*, vol. 30, no. 5, pp. 1424–1431, 2024. https://doi.org/10.1038/s41591-024-02908-9

[9] E. M. Miller, "Using continuous glucose monitoring in clinical practice," *Clin Diabetes*, vol. 38, no. 5, pp. 429–438, 2020. https://doi.org/10.2337/cd20-0043

[10] M. S. Reddy *et al.*, "Predicting tomorrow's ailments: How AI/ML is transforming disease forecasting," *ESP Journal of Engineering & Technology Advancements*, vol. 1, no. 2, pp. 188–200, 2021.

[11] A. Yahyaoui, A. Jamil, J. Rasheed, and M. Yesiltepe, "A decision support system for diabetes prediction using machine learning and deep learning techniques," in *2019 1st International Informatics and Software Engineering Conference (UBMYK)*, 2019, pp. 1–4. https://doi.org/10.1109/UBMYK48245.2019.8965556

[12] H. K. Apat and B. Sahoo, "LESP: A fault-aware internet of things service placement in fog computing," *Sustainable Computing: Informatics and Systems*, vol. 46, p. 101097, 2025. https://doi.org/10.1016/j.suscom.2025.101097

[13] E. F. Siddiqui, T. Ahmed, and S. K. Nayak, "A decision tree approach for enhancing realtime response in exigent healthcare unit using edge computing," *Measurement: Sensors*, vol. 32, p. 100979, 2024. https://doi.org/10.1016/j.measen.2023.100979

[14] J. Anand and B. Karthikeyan, "Dynamic priority-based task scheduling and adaptive resource allocation algorithms for efficient edge computing in healthcare systems," *Results in Engineering*, vol. 25, p. 104342, 2025. https://doi.org/10.1016/j.rineng.2025.104342

[15] V. Mani *et al.*, "A new blockchain and fog computing model for blood pressure medical sensor data storage," *Computers and Electrical Engineering*, vol. 102, p. 108202, 2022. https://doi.org/10.1016/j.compeleceng.2022.108202

[16] N. Alsharabi, A. Alayba, G. Alshammari, M. Alsaffar, and A. Jadi, "An end-to-end four tier remote healthcare monitoring framework using edge-cloud computing and redactable blockchain," *Computers in Biology and Medicine*, vol. 189, p. 109987, 2025. https://doi.org/10.1016/j.compbiomed.2025.109987

[17] S. Shukla, S. Thakur, S. Hussain, J. G. Breslin, and S. M. Jameel, "Identification and authentication in healthcare internet-of-things using integrated fog computing based blockchain model," *Internet of Things*, vol. 15, p. 100422, 2021. https://doi.org/10.1016/j.iot.2021.100422

[18] R. Yadav, P. Pradeepa, S. Srinivasan, C. S. Rajora, and R. Rajalakshmi, "A novel healthcare framework for ambient assisted living using the internet of medical things (IOMT) and deep neural network," *Measurement: Sensors*, vol. 33, p. 101111, 2024. https://doi.org/10.1016/j.measen.2024.101111

[19] B. Ahamed, S. Sellamuthu, P. N. Karri, I. V. Srinivas, A. M. Zabeeulla, and M. A. Kumar, "Design of an energy-efficient IOT device-assisted wearable sensor platform for healthcare data management," *Measurement: Sensors*, vol. 30, p. 100928, 2023. https://doi.org/10.1016/j.measen.2023.100928

[20] H. Wang *et al.*, "HealthAIoT: AIoT-driven smart healthcare system for sustainable cloud computing environments," *Internet of Things*, vol. 31, p. 101555, 2025. https://doi.org/10.1016/j.iot.2025.101555

[21] A. Marengo, A. Pagano, and V. Santamato, "An efficient cardiovascular disease prediction model through AI-driven IoT technology," *Computers in Biology and Medicine*, vol. 183, p. 109330, 2024. https://doi.org/10.1016/j.compbiomed.2024.109330

[22] S. M. Rajagopal, M. Supriya, and R. Buyya, "Leveraging blockchain and federated learning in Edge-Fog-Cloud computing environments for intelligent decision-making with ECG data in IoT," *Journal of Network and Computer Applications*, vol. 233, p. 104037, 2025. https://doi.org/10.1016/j.jnca.2024.104037

[23] A. Almalawi *et al.*, "Enhancing security in smart healthcare systems: Using intelligent edge computing with a novel Salp Swarm Optimization and radial basis neural network algorithm," *Heliyon*, vol. 10, no. 13, p. e33792, 2024. https://doi.org/10.1016/j.heliyon.2024.e33792

[24] D. M. Reoukadji, P. L. Bokonda, A. A. Madi, and I. Alihamidi, "Automatic Collection System for Medical Consultation," in *2024 4th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, FEZ, Morocco: IEEE, 2024, pp. 1–7. https://doi.org/10.1109/IRASET60544.2024.10549351

[25] Md Mehedi Hassain *et al.*, "Voice activated medicine reminder box with IoT health monitoring for old people and hospital," *European Journal of Engineering and Technology Research*, vol. 10, no. 2, pp. 22–30, 2025. https://doi.org/10.24018/ejeng.2025.10.2.3252

[26] B. G. Mohammed and D. S. Hasan, "Smart healthcare monitoring system using IoT," *Int. J. Interact. Mob. Technol.*, vol. 17, no. 1, pp. 141–152, 2023. https://doi.org/10.3991/ijim.v17i01.34675

[27] Analog Devices, Inc., "MAX30100 Datasheet and Product," 2025. Accessed: July 20, 2025. [Online]. Available: https://www.analog.com/en/products/max30100.html

[28] Texas Instruments, "ADS1292R data sheet, product information and support," 2025. Accessed: July 20, 2025. [Online]. Available: https://www.ti.com/product/ADS1292R

[29] Abdellah Abnoune, "Comment utiliser le capteur de température MLX90614 avec Arduino: Guide complet pour les débutants," Moussasoft, 2023. Accessed: July 20, 2025. [Online]. Available: https://www.moussasoft.com/utiliser-mlx90614-capteur-temperature-arduino/

[30] MicroPlanet, "HC-SR04 Module Ultrasonique Detection De Distance," 2025. Accessed: July 20, 2025. [Online]. Available: https://www.micro-planet.ma/produit/module-ultrasonique-detection-de-distance-hc-sr04/?srsltid=AfmBOorVzwgmcQomlWI_VaroJYyKk1sSI4YJod1pnjd6Y6VZMCa_wZtd

[31] WEMOS.cc., "LOLIN D1 mini," 2025. [Accessed: July 20, 2025]. [Online]. Available: https://www.wemos.cc/en/latest/d1/d1_mini.html

[32] C. Keskinoğlu and A. Aydın, "Full wireless goniometer design with activity recognition for upper and lower limb," *Microprocessors and Microsystems*, vol. 109, p. 105086, 2024. https://doi.org/10.1016/j.micpro.2024.105086

[33] A. Kelati, I. B. Dhaou, and H. Tenhunen, "Biosignal monitoring platform using wearable IoT," in *Proceedings of the 22st Conference of Open Innovations Association FRUCT*, in FRUCT'22. May 2018, Helsinki, Uusimaa, FIN: FRUCT Oy, 2018, pp. 332–337.

[34] S. Chowdhury *et al.*, "An IoT-based wearable healthcare monitoring device and medical emergency response system," in *2024 IEEE Students Conference on Engineering and Systems (SCES)*, 2024, pp. 1–5. https://doi.org/10.1109/SCES61914.2024.10652375

[35] A. Nishat and J. Muzaffar, "Securing web applications with OAuth 2.0, JWT, and multi-factor authentication," *Euro Vantage Journals of Artificial Intelligence*, vol. 1, no. 2, 2024.

[36] V. Gupta, S. Khera, and N. Turk, "MQTT protocol employing IOT based home safety system with ABE encryption," *Multimedia Tools and Applications*, vol. 80, pp. 2931–2949, 2021. https://doi.org/10.1007/s11042-020-09750-4

[37] N. Gupta, V. Naik, and S. Sengupta, "A firewall for Internet of Things," in *2017 9th International Conference on Communication Systems and Networks (COMSNETS)*, 2017, pp. 411–412. https://doi.org/10.1109/COMSNETS.2017.7945418

[38] Z. Zhao and X. Xu, "Research on the application of computer data encryption technology in cloud security," *IJET*, vol. 14, no. 4, pp. 75–78, 2022. https://doi.org/10.7763/IJET.2022.V14.1206

[39] D. M. Reoukadji, P. L. Bokonda, A. A. Madi, and I. Alihamidi, "Protecting patient privacy and data integrity with DAG technology for IoMT and EHR: A systematic review," in *2024 4th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, 2024, pp. 1–7. https://doi.org/10.1109/IRASET60544.2024.10549660

[40] Z. A. Jaaz, I. Y. Khudhair, and H. M. Mushgil, "A novel routing protocol-based data transmission to enhance the quality of service for Internet of medical things using 5G," *Int. J. Interact. Mob. Technol.*, vol. 17, no. 10, pp. 212–227, 2023. https://doi.org/10.3991/ijim.v17i10.38797

[41] M. Chen, Q. Zhu, M. Wu, and Q. Wang, "Modulation model of the photoplethysmography signal for vital sign extraction," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 4, pp. 969–977, 2021. https://doi.org/10.1109/JBHI.2020.3013811

[42] Z. Pamuk and C. Kaya, "Detection of heart rate variability from Photoplethysmography (PPG) signals obtained by Raspberry Pi microcomputer," *Sakarya University Journal of Computer and Information Sciences*, vol. 5, no. 1, pp. 104–120, 2022. https://doi.org/10.35377/saucis...1024414

[43] "MLX90614 Datasheet(PDF) – Melexis Microelectronic Systems." Accessed: Nov. 24, 2025. [Online]. Available: https://www.alldatasheet.com/datasheet-pdf/pdf/224153/MELEXIS/MLX90614.html

[44] P. O'Gorman and H. Knipe, "Distance measurement," Radiopaedia.org, 2021. https://doi.org/10.53347/rID-46916

[45] Pannmie, "🩸Diabetes: EDA |🌲Random Forest🌲 + HP⚙️," *Kaggle*, 2023. Accessed: July 15, 2025. [Online]. Available: https://www.kaggle.com/code/tumpanjawat/diabetes-eda-random-forest-hp

[46] Y. Li and J. Zhao, "Prediction of accumulated auto insurance claims based on improved XGBOOST modeling," *IJET*, vol. 16, no. 4, pp. 250–254, 2024. https://doi.org/10.7763/IJET.2024.V16.1289

[47] "Random Forest: The Ultimate Guide to Regression and Classification | by AI Wrld | Medium." Accessed: Nov. 24, 2025. [Online]. Available: https://medium.com/@adeevmardia/random-forest-the-ultimate-guide-to-regression-and-classification-33506d6cf865

[48] L. Zhang *et al.*, "Classification and regression with random forests as a standard method for presence-only data SDMs: A future conservation example using China tree species," *Ecological Informatics*, vol. 52, pp. 46–56, 2019. https://doi.org/10.1016/j.ecoinf.2019.05.003

[49] J. H. Friedman, "Greedy function approximation: A gradient boosting machine." *The Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, 2001. https://doi.org/10.1214/aos/1013203451

[50] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, California, USA, 2016, pp. 785–794. https://doi.org/10.1145/2939672.2939785

[51] S. I. Sherwani, H. A. Khan, A. Ekhzaimy, A. Masood, and M. K. Sakharkar, "Significance of HbA1c test in diagnosis and prognosis of diabetic patients," *Biomarker Insights*, vol. 11, p. 95, 2016. https://doi.org/10.4137/BMI.S38440

[52] E. Halabaku and E. Bytyçi, "Overfitting in machine learning: A comparative analysis of decision trees and random forests," *IASC*, vol. 39, no. 6, pp. 987–1006, 2024. https://doi.org/10.32604/iasc.2024.059429

[53] L. Zhou, Q. Zhu, Q. Chen, P. Wang, and H. Huang, "Predicting hospital outpatient volume using XGBoost: A machine learning approach," *Sci. Rep.*, vol. 15, no. 1, p. 17028, 2025. https://doi.org/10.1038/s41598-025-01265-y

[54] R. Ali, S. Lee, and T. C. Chung, "Accurate multi-criteria decision making methodology for recommending machine learning algorithm," *Expert Systems with Applications*, vol. 71, pp. 257–278, 2017. https://doi.org/10.1016/j.eswa.2016.11.034

[55] A. Martinez-Millana, M. Argente-Pla, B. Valdivieso Martinez, V. Traver Salcedo, and V. F. Merino-Torres, "Driving type 2 diabetes risk scores into clinical practice: Performance analysis in hospital settings," *J. Clin. Med.*, vol. 8, no. 1, p. 107, 2019. https://doi.org/10.3390/jcm8010107

[56] T. Saito and M. Rehmsmeier, "The precision-recall plot is more informative than the ROC Plot when evaluating binary classifiers on imbalanced datasets," *PLoS One*, vol. 10, no. 3, p. e0118432, 2015. https://doi.org/10.1371/journal.pone.0118432

[57] J. Anand and B. Karthikeyan, "Dynamic priority-based task scheduling and adaptive resource algorithms for efficient edge computing in healthcare systems," *Results in Engineering*, vol. 25, p. 104342, 2025. https://doi.org/10.1016/j.rineng.2025.104342

[58] M. D. Teja and G. M. Rayalu, "Optimizing heart disease diagnosis with advanced machine learning models: A comparison of predictive performance," *BMC Cardiovasc. Disord.*, vol. 25, p. 212, 2025. https://doi.org/10.1186/s12872-025-04627-6

[59] M. H. Tuama, "A comparative evaluation of random forest and XGBoost models for disease detection using medical indicators," *IJPS*, vol. 19, no. 1, pp. 11–18, 2025. https://doi.org/10.37648/ijps.v19i01.002

[60] M. Imani, A. Beikmohammadi, and H. R. Arabnia, "Comprehensive analysis of random forest and XGBoost performance with SMOTE, ADASYN, and GNUS under varying imbalance levels," *Technologies*, vol. 13, no. 3, p. 88, 2025. https://doi.org/10.3390/technologies13030088

[61] Z. Shao, M. N. Ahmad, and A. Javed, "Comparison of random forest and XGBoost classifiers using integrated optical and SAR features for mapping urban impervious surface," *Remote Sensing*, vol. 16, no. 4, p. 665, 2024. https://doi.org/10.3390/rs16040665

[62] C. Karunakaran, V. Niranjan, and A. S. Setlur, "Random forest and XGBoost-based ensemble models for colorectal cancer exome variant classification and web application deployment for early prediction," *Computational and Structural Biotechnology Reports*, vol. 2, p. 100063, 2025. https://doi.org/10.1016/j.csbr.2025.100063

7 AUTHORS

Dior Masrane Reoukadji is a Chadian computer and network engineer. He holds a BSc in Physical Matter Science and an MSc in Networks & Telecommunications systems. He is a PhD candidate in the Advanced Systems Engineering Laboratory at ENSA–Ibn Tofail University (Kenitra, Morocco). His work focuses on secure digital-health infrastructures for resource-constrained settings, including the Smart Medical Gate for automated vital-sign capture, privacy-preserving IoMT/EHR architectures using DAG blockchain, embedded electronics, and high-dimensional QKD for quantum-safe healthcare communications. His interests span hospital information systems, IoMT/edge computing, EHR, ML for clinical decision support, and cybersecurity (E-mail: dior.masranereoukadji@uit.ac.ma).

Olivier Mekila Mbayam is a PhD student in engineering sciences, focusing on energy systems in buildings. His research centers on optimizing energy consumption through smart systems to boost the energy efficiency of infrastructure. Before diving into academia, Mekila gained years of experience in the oil and construction industries as a mechanical engineer. This professional background helped him build strong expertise in managing complex technical systems, particularly those related to energy efficiency and industrial process optimization. Now, his research focuses on integrating advanced technologies into buildings to reduce their energy footprint while ensuring optimal resource management (E-mail: mekiolivier@gmail.com).

Imam Alihamidi holds a Ph.D. in Computer Science and Telecommunications and is a Research Professor at EMSI, affiliated with the Advanced Systems Engineering Laboratory and SMARTiLab. His work focuses on emerging technologies, particularly IoT, cyber-physical systems, AI, and blockchain integration in smart healthcare. A State Engineer in Networks and Telecommunications (ENSA Kenitra, 2018) and Ph.D. graduate from Ibn Tofail University, he also lectured there and contributed to international conferences. Beyond academia, he consults on Industry 4.0, cloud infrastructures, and healthcare information systems, with expertise in cybersecurity and IoT architectures.

Patrick Loola Bokonda is a Congolese (DRC) computer scientist specializing in AI. He earned his Master's degree and Ph.D. at Mohammed V University in Rabat, Morocco. Currently, he is an Associate Professor of Computer Science at the Haute École de Commerce de Kinshasa (HEC-Kin) in the Democratic Republic of the Congo. His work focuses on artificial intelligence, machine learning, and digital tools such as Open Data Kit (ODK) to improve data collection, hospital information systems, and information systems designed to enhance people's lives (E-mail: loola.bokonda@gmail.com).

Abdessalam Ait Madi earned a degree in electronics engineering education from ENSET Mohammedia. He completed his Master's and Ph.D. at the Faculty of Sciences and Technologies, Sidi Mohamed Ben Abdellah University (Fez), and later obtained his Habilitation from the Faculty of Sciences, Ibn Tofail University. He is currently an Associate Professor at the National School of Applied Sciences, Ibn Tofail University, Kenitra, Morocco. His research interests include information theory, channel coding, embedded systems, IoT technologies, and renewable energy (E-mail: abdessalam.aitmadi@uit.ac.ma).