Secure and Privacy-Preserving Automated End-to-End Integrated IoT-Edge-Artificial Intelligence-Blockchain Monitoring System for Diabetes Mellitus Prediction

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Abstract

Diabetes Mellitus, one of the leading causes of death worldwide, has no cure till date and can lead to severe health complications, such as retinopathy, limb amputation, cardiovascular diseases, and neuronal disease, if left untreated. Consequently, it becomes crucial to take precautionary measures to avoid/predict the occurrence of diabetes. Machine learning approaches have been proposed and evaluated in the literature for diabetes prediction. This paper proposes an IoT-edge-Artificial Intelligence (AI)-blockchain system for diabetes prediction based on risk factors. The proposed system is underpinned by the blockchain to obtain a cohesive view of the risk factors data from patients across different hospitals and to ensure security and privacy of the user’s data. Furthermore, we provide a comparative analysis of different medical sensors, devices, and methods to measure and collect the risk factors values in the system. Numerical experiments and comparative analysis were carried out between our proposed system, using the most accurate random forest (RF) model, and the two most used state-of-the-art machine learning approaches, Logistic Regression (LR) and Support Vector Machine (SVM), using three real-life diabetes datasets. The results show that the proposed system using RF predicts diabetes with 4.57% more accuracy on average compared to LR and SVM, with 2.87 times more execution time. Data balancing without feature selection does not show significant improvement. The performance is improved by 1.14% and 0.02% after feature selection for PIMA Indian and Sylhet datasets respectively, while it reduces by 0.89% for MIMIC III.

Keywords: Artificial Intelligence (AI), Blockchain, Diabetes Mellitus Type 2, Diagnosis,
1. Introduction

Diabetes Mellitus, commonly referred as diabetes, is one of the top 10 leading causes of deaths globally [1]. It is a metabolic disease in which body does not produce enough insulin or body cells do not respond to insulin in a proper way, leading to increased blood sugar levels [2]. There are three main types of diabetes, type 1 and type 2 diabetes mellitus, and gestational diabetes [3]. According to a report by the International Diabetes Federation, 537 million adults (i.e., 1 in every 10 people), between the ages of 20-79 years, worldwide were having diabetes in 2021 [4]. Furthermore, this number is predicted to reach 643 million by 2030 and 783 million by 2045. In 2021, diabetes was responsible for 6.7 million deaths and caused at least USD 966 billion in health expenditure [4].

The etiopathology of type 2 diabetes mellitus has been linked to dynamic interactions between lifestyle, medical conditions, hereditary, psychosocial, and demographic risk factors [3]. Diabetes if not treated at an early stage can lead to severe complications such as retinopathy, limb amputation, cardiovascular diseases, and neuronal disease [5]. In 2021, over 240 million adults with diabetes were undiagnosed (i.e., almost 1 in 2 diabetic) [6]. Consequently, machine learning-based diabetes prediction have gained an increased attention in the literature [7,8,9,10,11,12,13,14] for better prognosis/diagnosis support to the medical health professionals and public health organizations [15]. Disparate work in literature focuses on evaluating machine learning algorithms for different diabetes datasets under non-unified experimental setups. However, to the best of our knowledge, there is no work that proposes an end-to-end IoT-edge-Artificial Intelligence (AI)-blockchain integrated computing system for diabetes monitoring and prediction. This paper aims to address this void. The proposed system analyzes diabetes risk factors using medical sensors/devices and predict the incidence of diabetes in an individual using the most accurate machine learning model. Furthermore, the proposed system employs edge computing to transform the risk factors data collected from IoT devices and send preprocessed data to blockchain. Blockchain [16] stores the medical records of the patients as well the machine learning model parameters and prediction results in a distributed and replicated ledger. This is based on the potential of blockchain in healthcare industry [17,18,19]. The consensus, replication, traceability, and distributed features of blockchain aids in security, privacy, audit trail, transparency, and trust in the proposed system.

The main contributions of this paper are as follows.

- We propose an end-to-end automated IoT-edge-AI-blockchain system for diabetes prediction based on risk factors.

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We present a comparative list of medical sensors, devices and methods used to measure the values of diabetes risk factors; hypertension, obesity, cholesterol level, depression, serum uric acid, sleep duration, physical activity, and glucose level.

- We propose an implementation workflow for the proposed system.

- The performance of the proposed system is evaluated and compared with the most used machine learning approaches for diabetes prediction in terms of accuracy, precision, recall, F-measure, Area Under the Receiver Operating Characteristics (ROC) Curve (AUC), and execution time.

The rest of the paper is organized as follows. Section 2 summarizes the related work on machine learning-based diabetes prediction. The proposed automated end-to-end IoT-edge-AI-blockchain system for diabetes mellitus prediction is explained in Section 3. Section 4 discusses the implementation of the proposed system. Numerical experiments and comparative performance results are provided in Section 5. Finally, Section 6 concludes the paper with future research directions.

2. Related Work

Several works in the literature have used machine and deep learning algorithms for diabetes prediction [7, 8, 9, 10, 11, 12, 13, 14]. Table 1 summarizes these works and presents the dataset, preprocessing techniques, feature selection approaches, and machine/deep learning algorithms used in each work. However, these works only focus on stand-alone diabetes prediction and do not propose an end-to-end diabetes prediction system. In contrast, we propose a secure and privacy-preserving end-to-end integrated IoT-edge-AI-blockchain monitoring system for diabetes prediction.
Table 1: Summary of Related Work on Diabetes Prediction.

| Work | Dataset | Features | Observations | Data balancing | Feature selection | Algorithms | Evaluation metrics |
|------|---------|----------|--------------|----------------|------------------|------------|--------------------|
| [7]  | Private: EHRs acquired from 5 hospitals in Saudi Arabia between 2016 – 2018 | DOB, gender, height weight, hypertension, fasting plasma glucose, haemoglobin A1C, HDL, LDL, physical activity, diagnosis start date, and primary and secondary diagnosis codes and full names | 3000 patients | Data is already balanced | Permutation importance and hierarchical clustering | LR, SVM, DT, RF, EMV<sup>*</sup> | Accuracy, precision, recall, and F-measure |
| [8]  | Private: EHRs data collected at preventive healthcare examinations of healthy population in 10 Slovenian primary healthcare institutions | Related to FINDRISC questionnaire and medical history | 27050 patients | x | x | Linear regression, Glmnet, RF, XGBoost, and lightGBM | AUC and RMSE |
| [9]  | Private: EHRs collected between 2013 – 2018 from a private medical institute, Hanaro Medical Foundation, in Seoul (South Korea) | Related to blood test, anthropometric measurements, diagnostics results, and questionnaire answers | 253359 subjects (68.1% normal, 4.3% diabetics, and 27.6% prediabetes) | Majority undersampling and SMOTE | ANOVA, chi-squared test and recursive feature elimination | LR, RF, SVM, XGBoost, stacking<sup>†</sup>, soft voting<sup>†</sup>, and confusion matrix-based ensemble<sup>†</sup> | Accuracy, precision, recall, F-measure, MCC, and KC |
| [10] | D1: Cross-sectional diabetes survey in Saudi Arabia D2: NHANES D3: PIMA Indian | D1: region, age, gender, BMI, waist size, physical activity, diet, blood pressure, and family history of diabetes D2: smoking, diet, blood pressure, BMI, gender, and region D3: ↑ | D1: 4896 (990 diabetics and 3906 non-diabetics) D2: 4918 (1709 prediabetes and 3209 diabetics) D3: 768 (268 diabetics and 500 non-diabetics) | SMOTE | Pearson chi-square test | BPM, AP, DF, LD-SVM, DJ, boosted DT, and NN | Accuracy, precision, recall, F-measure, and AUC |
| [11] | PIMA Indian | ↑ | 768 (268 diabetics and 500 non-diabetics) | x | Different combinations based on manual inspection | LR and DT | Accuracy, error rate, AIC, BIC, R2, and log likelihood |
| [12] | PIMA Indian | ↑ | 768 (268 diabetics and 500 non-diabetics) | x | PCA, k-means clustering, and importance ranking | NB, RF, and DT | Accuracy, precision, sensitivity, specificity, F-measure, and AUC |
| Study                                                                 | Characteristics                                                                 | Participants | Methodology                                      | Evaluation Measures                                                                 |
|----------------------------------------------------------------------|---------------------------------------------------------------------------------|--------------|-------------------------------------------------|-------------------------------------------------------------------------------------|
| Henan rural cohort study: participants aged between 18 – 79 years were recruited from five rural areas in Henan province of China between July 2015 and September 2017 | Related to socio-demographic characteristics, information on physical examination, and laboratory tests | 39259 participants | SMOTE | Iterative approach | LR, CART, ANN, SVM, RF, and GBM | AUC, sensitivity, specificity, positive prediction value, negative prediction value, and area under precision-recall curve |
| CBHS health funds company in Australia: hospital admissions data between 1995 – 2018 | Age, gender, and smoking status | 2056 (1028 diabetics and 1028 non-diabetics) | Data is already balanced | X | LR, kNN, SVM, NB, DT, RF, XGBoost, and ANN | Accuracy, precision, recall, F-measure, and AUC |

EHRs – Electronic Health Records; LR – Logistic Regression; SVM – Support Vector Machine; DT – Decision Tree; RF – Random Forest; EMV – Ensemble Majority Voting; ∗ – EMV consists of LR, SVM, and DT; Glmnet – Regularized Generalized Linear Model; XGBoost – Extreme Gradient Boosting; lightGBM – light Gradient Boosting Machine; † – ensemble algorithms use LR, RF, SVM, and XGBoost; BPM – Bayes Point Machine; AP – Average Perceptron; DF – Decision Forest; LD-SVM – Locally Deep SVM; DJ – Decision Jungle; NN – Neural Network; NB – Naïve Bayes; CART – Classification and Regression Tree; GBM – Gradient Boosting Machine; kNN – k Nearest Neighbor; AUC – Area Under the ROC Curve; RMSE – Root Mean Squared Error; MCC – Mathews Correlation Coefficient; KC – Kappa’s Coefficient; AIC – Akaike’s Information Criteria; BIC – Bayesian Information Criteria; PCA – Principal Component Analysis; SMOTE – Synthetic Minority Oversampling Technique; NHANES – National Health and Nutrition Examination Survey; HDL – High Density Lipoprotein; LDL – Low Density Lipoprotein; § – Before data preprocessing; † – Not performed
3. Proposed Automated End-to-End Integrated IoT-Edge-Artificial Intelligence-Blockchain Monitoring System for Diabetes Mellitus Prediction

The overall architecture of our proposed end-to-end system for diabetes prediction is presented in Figure 1. The main components of the architecture are as follows:

- **User’s Diabetes Risk Factors Monitoring**: A user, i.e., a patient and/or an external participant, communicates with the application to know about his/her risk for incidence of diabetes. A user is connected to different medical sensors and devices such as glucose monitor, blood pressure monitor, sleep tracker, and physical activity tracker. These sensors and devices measure the health data of the user, related to diabetes risk factors, and send them to the application.

- **Edge Computing**: The risk factors data collected using different medical sensors and devices is sent to edge servers to transform it into a format that can be used by a machine learning algorithm. The data is then sent to blockchain network.

- **Artificial Intelligence Diabetes Prediction Application**: The front end of the application allows external users to upload their health data related to diabetes risk factors such as glucose level, blood pressure, sleeping habits, physical activity, smoking status, and alcohol consumption. This data can be uploaded manually by the user to the mobile application or by using data from the blockchain. The uploaded data is fed to the machine learning model in the back end for predicting the risk of diabetes, i.e., whether the user belong to either diabetes or non-diabetes class. The prediction result is displayed to the user.

![Architecture Overview of Proposed Automated End-to-End Integrated IoT-Edge-Artificial Intelligence-Blockchain Monitoring System for Diabetes Mellitus Prediction.](image)
• **Blockchain:** This component connects all the network participants in a peer-to-peer manner. The network participants involve allied health professionals, patients, pharmacy, and medical experts. Each participant is authenticated by a certificate authority. The medical records and the health data of the patients are uploaded to the blockchain ledger. The ledger is replicated over multiple hospitals.

Diabetes, i.e., increased glucose levels, is associated with different demographic, psychosocial, hereditary, medical conditions, and lifestyle related risk factors [2, 3]. The values of these risk factors can be either self-reported by the patients/external users or measured using bio-sensors, wearable devices, or medical tests. The self-reported risk factors include age, gender, ethnicity, smoking, alcohol consumption, and family history of diabetes. On the other hand, the measurable risk factors include hypertension, cardiovascular diseases, obesity, abnormal cholesterol level, depression, serum uric acid, sleep duration, and physical activity. Different bio-sensors, devices and methods, used to measure the values of these risk factors, are explained in the following subsections. In addition, the two main components of the system architecture, i.e., blockchain and AI-based diabetes prediction, are explained.

3.1. User’s Diabetes Risk Factors Monitoring

3.1.1. Hypertension Monitoring

Hypertension is a medical condition where the blood pressure in the arteries remains elevated, i.e., a systolic blood pressure greater than or equal to 140 mmHg and a diastolic blood pressure greater than or equal to 90 mmHg [20]. Individuals having systolic/diastolic pressures greater than or equal to 140/90 mmHg are at increased risk of developing diabetes compared to those having pressure less than 140/90 mmHg as shown in Figure 2. Table 2 lists different hypertension monitors along with their measurement method, accuracy, and approximate cost in US dollars.

![Figure 2: Association Between Hypertension and Prevalence of Type 2 Diabetes Mellitus.](image)

| Device | Performance | Approximate cost (in US Dollars) |
|--------|-------------|---------------------------------|
| Omron Evolv (HEM-7600T-E) [21] | Mean difference compared to standard mercury sphygmomanometer test [22]: <br>-0.1 ± 5.0 mmHg (for systolic blood pressure) <br>-0.2 ± 4.1 mmHg (for diastolic blood pressure) | 136 [23] |

Table 2: Comparison Between Different Hypertension Monitoring Devices.
3.1.2. Obesity Monitoring

Obesity is characterized by excessive amount of body fat and is often defined in terms of Body Mass Index (BMI), waist circumference, and/or waist-hip ratio \[30\]. It is strongly associated with the prevalence of type 2 diabetes. Table 3 shows different methods and devices used to measure obesity with their strengths and weaknesses.

| Method/device                        | Strengths                                      | Weaknesses                                                                 |
|--------------------------------------|------------------------------------------------|----------------------------------------------------------------------------|
| Statistical BMI calculation [31]     | Quick, cost-effective, and easy                | Not accurate for elderly, muscular, and pregnant individuals               |
| Skinfold calipers [32]               | Easy to use, portable, and cost-effective      | Accuracy depends on the skill of the person using the caliper              |
| Smart weighing scales [33]           | Quick and easy                                 | Reliability of the result depends on the condition of the individual whose measurement is taken (for instance, hydrated or dehydrated), some accurate scales are costly |
| Hydrodensitometry [34]              | Accurate and reliable                          | Costly and not suitable for children and elderly person as it requires the individual to be submerged in water for 5-7 seconds repeatedly 2-3 times |
| Air displacement plethysmography [35] | Quick, accurate, reliable, and suitable for any age | Costly                                                                    |
| Dual energy x-ray absorptiometry [36]| Quick, precise, and reliable                  | Costly                                                                    |

3.1.3. Cholesterol Level Monitoring

Abnormal level of cholesterol and triglycerides increases the risk of type 2 diabetes prevalence. In particular, low level of high-density lipoproteins (HDL) and elevated level of low-density lipoproteins (LDL) leads to the development of diabetes \[37\]. The standard method to measure the cholesterol level is the lipid panel test (also known as lipid profile test) \[38\]. This test determines the levels of triglycerides, total, LDL, and HDL cholesterols in an individual. Recently, several portable devices have been developed to measure cholesterol level. Table 4 provides a summary on the performance and cost of these devices.

| Device               | Performance of variation | (Coefficient of variation) | Approximate cost (in US Dollars) |
|----------------------|--------------------------|-----------------------------|----------------------------------|
| EasyTouch [39]       | Not reported             | 60 [40]                     |                                  |
| BeneCheck Plus [41]  | Not reported             | 136 [42]                    |                                  |
3.1.4. Depression Monitoring

Depression is a medical condition that negatively affects the feelings, thoughts, and actions of an individual. It has a strong association with the prevalence of type 2 diabetes [43]. Depression is generally measured using clinical rating scales such as Beck’s Depression Inventory (BDI), Center for Epidemiological Studies – Depression scale (CES-D), and Zung Self-Rating Depression Scale (SDS) [44]. Figure 3 shows the normal score ranges for these tests and the ranges that lead to prevalence of diabetes.

![Depression Monitoring Diagram](image)

Figure 3: Association Between Depression and Prevalence of Type 2 Diabetes Mellitus.

3.1.5. Serum Uric Acid Monitoring

Serum uric acid is a waste product generated by the body during the purines breakdown process. An individual having a serum uric acid level >370 µmol/l is on high risk of developing type 2 diabetes [45]. Uric acid test is commonly used to measure the amount of uric acid either using blood or urine sample [46]. Recently, several test meters have been introduced to measure serum uric acid level. Table 5 shows a comparison between these meters.

| Method/device                      | Performance (Coefficient of variation) | Approximate cost (in US Dollars) |
|------------------------------------|----------------------------------------|---------------------------------|
| Smartphone as electrochemical analyzer [47] | Low concentration: 4.1%<sup>*</sup>    | Not available                   |
|                                    | Mid concentration: 2.47%<sup>*</sup>   |                                 |
|                                    | High concentration: 1.87%<sup>*</sup>  |                                 |
| EasyTouch [39]                     | 27.2% <sup>[48]</sup> (Not acceptable)<sup>†</sup> | 60 [40]                        |
| UAsure [49]                        | 25.9% <sup>[48]</sup> (Not acceptable)<sup>†</sup> | 64 [50]                        |
| BeneCheck Plus [41]                | 9.5% <sup>[48]</sup> (Acceptable)<sup>†</sup> | 136 [42]                       |
| HumaSens<sup>pre</sup> [51]        | 11.5% <sup>[48]</sup> (Acceptable)<sup>†</sup> | 52 [52]                        |
| Liquid chromatography mass spectrometry [53] | 0.01 – 3.37%<sup>*</sup> <sup>[54]</sup> | Not available                   |

<sup>*</sup>Average; <sup>†</sup>According to College of American Pathologists

3.1.6. Sleep Duration Monitoring

The quantity of sleep during night time is highly associated with the prevalence of type 2 diabetes [2]. As shown in figure [4] compared to 6-8 hours of night time sleep an individual
with a shorter sleep duration (<6 hours/night) and a longer sleep duration (>8 hours/night) are at higher risk of developing diabetes. In addition, napping during the day can also lead to prevalence of diabetes (figure 4). Table 6 summarizes different tests, devices, and applications used for tracking sleep. It shows the performance of each test/device/application along with its cost in USD.

![Figure 4: Association Between Sleep Duration and Prevalence of Type 2 Diabetes Mellitus.](image)

Table 6: Comparison Between Different Sleep Duration Monitoring Tests and Devices.

| Type     | Test/device               | Performance                                                                 | Approximate cost (in USD) |
|----------|---------------------------|-----------------------------------------------------------------------------|---------------------------|
| Non-invasive | Polysomnography test [54] | Sensitivity: 0.957*  
Specificity: 0.532*  
Accuracy: 0.904*  
Cohen’s kappa: 0.495* [54] | 943 – 2,798 [55] |
| Wearable | ÖURA ring [56]             | Sensitivity (to detect sleep): 96%  
Specificity (to detect wake): 48%* [57] | 299-399 [56] |
| Wearable | Fitbit Flex [58]           | 97.46% accuracy [59]                                                        | 100 [59]                 |
| Wearable | Fitbit Charge HR [60]      | Overestimates the sleep duration [61]                                       | 65.39 [62]               |
| Wearable | Polar A370 fitness tracker [63] | **Age group (mean ± SD): 11 ± 0.8**  
Sensitivity*: 0.93  
Specificity*: 0.77  
Accuracy*: 0.91 | 163 [63] |
| Wearable | Actiwatch 2 [65]           | **Age group (mean ± SD): 11 ± 0.8**  
Sensitivity*: 0.93  
Specificity*: 0.68  
Accuracy*: 0.90 | Not available |
| Wearable | Fitbit Alta HR [66]        | All sleep  
Sensitivity: 0.96 ± 0.02  
Specificity: 0.58 ± 0.16  
Accuracy: 0.90 ± 0.04 [67] | 270 [68] |
| Wearable | Withings Pulse [69]        | 98.1% accuracy [69]                                                         | 100 [69]                 |
| Wearable | Misfit Shine [59]          | 96% accuracy [59]                                                           | 100 [59]                 |
| Wearable | Jawbone Up24 [70]          | 97.25% accuracy [59]                                                        | 100 [59]                 |
3.1.7. Physical Activity Monitoring

Physical inactivity can lead to obesity and depression, resulting to prevalence of type 2 diabetes [2]. An individual performing 30-60 minutes of exercise 3 – 4 times/week can be considered as physically active. Table 7 summarizes different devices to track physical activity.

Table 7: Comparison Between Different Physical Activity Monitoring Devices.

| Type          | Device                      | Performance (Accuracy) | Approximate cost (in US Dollars) |
|---------------|-----------------------------|------------------------|----------------------------------|
| Waist-based   | Fitbit One [74]             | >90% [75]              | 70 [76]                          |
| Waist-based   | Omron HJ-321 [77]           | >90% [75]              | 67.25 [78]                       |
| Waist-based   | Sportline 340 Strider [79]  | >90% [75]              | 22 [80]                          |
| Wrist-based   | Fitbit Force [81]           | <90% [75]              | Not available                     |
| Ankle-based   | StepWatch activity monitor  [82] | Non-running activities: >95% Running activities: 74.4% [75] | Not available                     |
| Mobile phone  | Apple iPhone 5 [83]         | <90% [75]              | Obsolete                          |
| Mobile phone  | Samsung Galaxy S4 [84]      | <90% [75]              | 305 [85]                         |

3.1.8. Glucose Level Monitoring

Diabetes is characterized by elevated glucose level. For instance, an individual having fasting plasma glucose level less than 100 mg/dl is non-diabetic, whereas the one having level between 100-125 mg/dl is considered as pre-diabetic and having fasting plasma glucose level greater than 125 mg/dl is diabetic [86]. Table 8 compares different invasive and non-invasive glucose monitoring devices.

Table 8: Comparison Between Different Glucose Level Monitoring Devices.

| Type          | Device                                                      | Performance                                                | Approximate cost (in US Dollars) |
|---------------|-------------------------------------------------------------|------------------------------------------------------------|----------------------------------|
| Non-invasive  | Wearable-band type visible-near infrared optical [87]       | Average correlation coefficient between actual and measured glucose: 0.86 [87] | Not available                     |
| Non-invasive  | Triple-pole complementary split ring resonator-based microwave bio-sensor [88] | Sensitivity: 6.2 dB/(mg/ml) [88]                          | Not available                     |
| Invasive      | EasyTouch [89]                                             | Not reported                                               | 60 [40]                          |
| Invasive      | BeneCheck Plus [41]                                        | Not reported                                               | 136 [42]                         |

3.2. Artificial Intelligence Diabetes Prediction System

In this section, we describe the workflow of our proposed AI system to develop the machine learning model for diabetes prediction as shown in Figure 5. It explains the method used to train or update the training of the system model and predict the incidence/prevalence of diabetes. The following explains the workflow of the training/update training and prediction in detail.
• **Data collection for model creation:** in this stage medical records, laboratory results, contextual and social are collected. The inclusion of the risk factors in the dataset should be verified. The collected data is then required to be aggregated. The diabetes class labels should be defined. For instance, all the observations in the dataset having fasting plasma glucose level less than 100 mg/dl can be labeled as a non-diabetic class, whereas all having level between 100-125 mg/dl can be labeled as a pre-diabetic class and all having fasting plasma glucose level greater than or equal to 125 mg/dl can be labeled as a diabetic class. This can be done with the help of an expert’s advice.

• **Data preprocessing:** which involves handling missing values, removal of outliers, data scaling, and feature selection. The missing values can be treated by either removing the corresponding observations or adding synthetic values. Synthetic values can be generated using statistical (mean/mode/median) or machine learning (kNN imputation and rpart) approaches [89]. Data scaling is achieved through normalization and/or standardization. The numerical features having varying ranges should be normalized. This is because the model could be biased towards the feature with a bigger range 90. For example, the range for BMI is 18.2-67.1, whereas that for plasma glucose is 44-199. In feature selection, the features that do not contribute to diabetes are excluded to avoid overfitting the model at its development stage. For instance, features such as data sequence number, hospital ID, time, and date should be removed. All the features (diabetes risk factors) available in the dataset can be used or a subset of features can be selected by applying feature selection algorithms [91] or taking an expert’s advice or using a hybrid approach. In our proposed system we use Recursive Feature Elimination [92] which selects the set of features which are more relevant to the incidence of diabetes.

• **Data splitting:** the data is split for training (model development) and testing. This is done by dividing the dataset into 70% and 30% for training and validation respectively.

• **Model Development:** k-fold cross-validation technique [93] is used to develop the model with the preprocessed training data. In the proposed system, we use decision-tree random forest (RF) classification model [94] as it is the top-used algorithm in the diabetes literature [7, 8, 9, 10, 11, 12, 13, 14].

• **Model Evaluation:** The developed model is evaluated using validation data in terms of accuracy, precision, recall, F-measure, ROC, AUC, and execution time. F-measure is an important metric to evaluate the performance of machine learning model when trained using an imbalance dataset. This is because, F-measure can reveal ability of the model to detect both majority and minority classes [95].

• **Diabetes Prediction:** The developed machine learning algorithm after evaluation is used to predict the incidence or diagnosis the prevalence of diabetes based on the risk factors data.
3.3. Secure and Privacy-Preserving Blockchain-based End-to-End System

To develop the patient-centric blockchain-based end-to-end diabetes prediction system, we choose the multi-ledger-based blockchain architecture that provides configurable access control rights and facilitates the development of a separate ledger for collaborating allied health professionals [96]. Regarding the type of blockchain network, i.e. permissioned or permissionless [97], we select the permissioned network. This is because of the following disadvantages of the permissionless network: 1) unauthorized participation in the network leading to impersonate account holders, 2) clear transaction data in the ledger accessible to each network participants revealing sensitive patients’ data, 3) slow network throughput hindering real-time patient’s treatment, and 4) the need of paying transaction execution fees and mining rewards limiting the usability of the network. To enhance the data privacy where the medical data of a patient is only visible to some authorized hospitals in the network, authorized access, and improved performance, the multi-ledger-based architecture is selected. Table 9 shows how blockchain addresses different security and privacy issues. Our blockchain health information system network consists of participants, assets, transactions, and events. Table 10 shows the different types of participants, assets, transactions, and events that will be used in our system along with their description.

Table 9: Security and Privacy Analysis using Blockchain.

| Issue          | Blockchain solution                                                                 |
|----------------|--------------------------------------------------------------------------------------|
| Data confidentiality | The private and sensitive health data records can be only accessed by authorized network participants based on access control rights defined in the blockchain. A transaction for unauthorized access will not be validated by the network participants. |
| Data integrity  | Health data records are stored in blocks and each block is linked to the previous one using a cryptography mechanism. Modifying existing data in a block is computationally very expensive as the attacker has to change all the subsequent blocks in each copy of the ledger. Furthermore, any modification if performed will be logged in the ledger and can be easily traced. |
| Data repudiation | Data update and query events are recorded in immutable ledger after validation ensuring fraud denials. |
Data audit

The replicated, time-stamped and immutable ledger ensures efficient, trusted, and integral auditing.

Data access control

Access control rights for health data records in blockchain can be defined using smart contracts for secure access by authorized participants.

Table 10: Description of Participants, Assets, Transactions, and Events for the Proposed Blockchain network.

| Name                  | Description                                                                                                                                                                                                 |
|-----------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Participants          |                                                                                                                                                                                                             |
| Hospitals             | They are responsible for uploading medical records to the blockchain network, validating healthcare transactions, and responding to the data retrieval query. They store the copy of the ledger.                                    |
| Allied health profes- | They are the doctors and nurses registered with the hospitals. They are responsible for updating patients’ medical records based on symptoms, diagnosis, treatments, and medications. They can also update the laboratory and pathological results. In addition, they can query the medical records from the ledger by performing transactions. |
| Pharmacists           | They are responsible for updating the information related to the medications, bills, and insurance claims. This is by performing transactions. In addition, they can query patient’s records from the ledger.                                      |
| Patients              | They are the diabetic and pre-diabetic patients registered with the hospitals. They can query their medical data and update contextual and lifestyle data to the blockchain network by performing transactions. The patients can enter the data into the network using mobile phones. |
| External users        | They are the participants not necessarily registered with the hospitals. They can insert their lifestyle, medical conditions, hereditary, psychosocial, and demographic data to predict the development of diabetes.                            |
| Assets                |                                                                                                                                                                                                             |
| Laboratory and pathol- | This asset includes the laboratory and pathological test data such as blood and urine reports, x-rays, MRIs, ultrasound, endoscopy, fasting plasma glucose, uric acid level, etc. These data are updated by the hospitals in the blockchain network. The data is made available to the corresponding patient upon a data retrieval query. |
| Medical condition data (by hospitals) | This asset includes the medical condition data such as symptoms, diagnosis, medications, treatments, and vitals, i.e., heart rate, blood pressure, oxygen level, cholesterol level, and BMI. These data are sent as transactions for an update in the blockchain network. The data is updated in the ledger by the hospital if found valid. |
| Social and contextual data (by patients) | This asset includes the social and contextual data such as age, gender, family history of diabetes, history of heart disease, depression, ethnicity, geographical location, smoking habits, alcohol consumption, diet, sleep duration, physical activity, educational level, and socioeconomic status. These data are sent as transactions by the patients for ledger updates. |
| Risk factors data (by external users) | This asset includes the diabetes risk factors data such as lifestyle, medical condition, hereditary, psychosocial, and demographic. These data are sent by the external users as transactions for the prediction of diabetes incidence. |
| Transactions          |                                                                                                                                                                                                             |
| Medical records update (by hospitals) | This transaction involves the update of the patient’s medical records by the hospitals to the blockchain ledger.                                                                                           |
| Laboratory and patholog- | This transaction involves the update of the patient’s laboratory and pathological results by the hospitals to the blockchain ledger.                                                                          |
| Social and contextual data update (by patients) | This transaction involves the update of the social and contextual data by the patients to the blockchain ledger.                                                                                           |
| Query (from patients to hospitals) | This transaction involves the data retrieval request by the patient to the registered hospital for his/her medical data.                                                                                  |
| Response to query (from hospitals to the patients) | This transaction involves the response from the hospital to the data retrieval query made by the patient.                                                                                           |
Transactions
Risk factors data (from external users to AI-based prediction system)
This transaction involves the risk factors data send by the external user as transactions for the prediction of diabetes incidence. The prediction request to the AI-based system will be recorded as a transaction in the ledger.

Transactions
Risk of diabetes incidence (from AI-based prediction system to the external users)
This transaction involves the prediction result by the development of diabetes. This data is used by the hospitals to develop a prevention plan.

Events
Patient’s medical records update (to patients)
The patient is notified about his/her records being added to the ledger by the corresponding hospital. This notification helps the patient to be up-to-date with his/her records.

Events
Patient’s laboratory and pathological results update (to patients)
The patient is notified about his/her laboratory and pathological results being added to the ledger by the corresponding hospital. This notification helps the patient to be up-to-date with his/her results.

Events
Patient’s social and contextual data update (to hospitals)
The hospital receives the social and contextual data transaction from the patient requesting to be added to the ledger. Upon validation, the data is added to the ledger.

Events
External user’s risk factors data update (to hospitals)
The hospital receives the risk factors data transactions by the external to update the ledger.

Events
External user’s prediction update (to hospitals)
The hospital updates the prediction results of the AI-based prognosis/diagnosis system in the blockchain ledger. This will aid in the development of a nationwide prevention plan.

Figure 6 shows the blockchain usage in our end-to-end AI-based prognosis/diagnosis support system for healthcare management. In addition to the network participants described in Table 10, the system consists of a certificate authority (CA), a medical expert, and an AI-based prognosis/diagnosis support system. The CA works as both a system administrator by removing malicious nodes from the network and an authority management entity by generating and distributing digital certificates. A participant’s public-private key pair is also generated by the CA. The public-private key pair for each participant is linked to the participant ID, a secret PIN code set by the participant, and the participant identity proof. In a situation where the participant loses his/her public-private key pair, a new pair is generated by the CA after authenticating the participant ID, secret PIN code, and identity proof. Each network participant, i.e., patient, allied health professionals, pharmacists, and external users, is identified using an identity number. For instance, a patient is identified by the patient ID whereas a doctor is identified by the doctor ID. A medical expert is responsible for annotating the diabetes risk factors and class labels to the medical records data present in the ledger. In addition, the medical expert will give feedback on the performance of the AI system when asked for an opinion. The expert’s feedback is recorded as a transaction in the ledger. The AI-based prognosis/diagnosis support system consists of classification learning models for the prediction of the development of diabetes in the blockchain participants and the external users based on the entered risk factors data. Table 11 shows the data and the corresponding attributes used in the proposed system.

Table 11: Health Data and Corresponding Attributes used in the Proposed System.

| Data                          | Attributes                                      |
|-------------------------------|-------------------------------------------------|
| Laboratory and pathological results | X-rays, MRIs, CT scans, blood report, and urine report |
Medical records | File number, patient ID, patient name, age, gender, nationality, national identity number, medical insurance number, contact details, patient name, height, weight, waist circumference, body temperature, blood pressure, the reason for attendance, patient medical history, family medical history, allergies, symptoms, diagnosis, point of care testing (random blood sugar, urine dip, pregnancy test), medications
---|---
Social and contextual data | Age, diet, sleeping pattern, heart rate, physical activity, smoking habits, alcohol consumption
Risk factors data | High-level serum uric acid, sleep quality/quantity, smoking, depression, cardiovascular disease, dyslipidemia, hypertension, aging, ethnicity, family history of diabetes, physical inactivity, and obesity

4. Implementation of Proposed Automated End-to-End Blockchain Artificial Intelligence-System for Diabetes Mellitus Prediction

In this section, the implementation of the system is discussed. The system operates through two main functions: 1) $DP(\text{user}_\text{risk})$ which allows end-users to get diabetes prediction from the system through a front-end device (e.g. smart phone), and 2) $DPMT(df_{\text{risk}})$, the diabetes prediction model trainer, which trains or updates the system’s AI model by using new labelled data.

For the first operative function, $DP(\text{user}_\text{risk})$, the implementation diagram is shown in Figure 7(a). The risk factor data (which is unlabelled) is collected from a data source $D_{\text{src}}$, which is accessed using the Blockchain interface. This is because the users’ health records including diabetes risk factors data are stored using a Blockchain platform. The raw risk factor data $df_{\text{risk}}$ is fed as an input to the data transformation component for preprocessing. Data transformation is performed by edge servers. The preprocessed data frame $df'_{\text{risk}}$ is then passed as input to the current Machine Learning model for diabetes prediction. The result of the prediction is sent back to the end-user device and to the Blockchain ledger.

For the second operative function, $DPMT(df_{\text{risk}})$, the system is upgraded using previous modeling data and the new data generated by users and/or health professionals, which is already labelled by the health professionals and stored in the Blockchain ledger, as shown in Figure 7(b). This new training data, $D_{\text{src}2}$, is extracted from the Blockchain data source to be fed as input to the data transformation component for preprocessing. The preprocessed data is then divided into training $df_{\text{tr}}^{\text{risk}}$ and validation $df_{\text{vd}}^{\text{risk}}$ datasets. The selected Random Forest model $f(risk)$ is trained again using $df_{\text{tr}}^{\text{risk}}$. The performance of the model is evaluated using $df_{\text{vd}}^{\text{risk}}$. The model development is a feedback control process where the model is tuned using hyperparameter tuning unless the desired performance is obtained. The diabetes prediction error $e_{\text{risk}}$ obtained from the evaluation of the prediction model is fed back to tune the hyperparameters. The tuned model $f^*(\text{risk})$ is deployed in the system for predicting accurately the risk of diabetes occurrence in users. Consequently, the diabetes prediction function, $DP(\text{user}_\text{risk})$, uses the deployed model to predict the risk of diabetes.

5. Method

In this section, we present the methodology used to evaluate our proposed system. We use three public diabetes datasets that include as many diabetes risk factors as possible: PIMA Indian [98], Sylhet [99], and MIMIC III [100]. The datasets are then explored to identify the
Figure 6: Proposed Blockchain and Artificial Intelligence Integrated Monitoring System for Prediction of Diabetes Mellitus.

Figure 7: Implementation of the Proposed End-to-End Automated Artificial Intelligence (AI)-Blockchain Systems for Diabetes Monitoring.
correlations between the risk factors and the occurrence of diabetes in patients and users. Datasets are preprocessed using cleaning and normalization, by removing the observations with missing values, and normalizing values across the observations, respectively. We evaluate the performance using the most used machine learning models in the literature on diabetes prediction, namely Random Forest (RF), Logistic Regression (LR) \cite{101}, and Support Vector Machine (SVM) \cite{102}, with and without feature selection, with and without balancing using HealthEdge (https://github.com/alain-hennebelle/HealthEdge). Recursive Feature Elimination, Cross-Validated (RFECV) feature selection algorithm, and Synthetic Minority Oversampling Technique (SMOTE) balancing are used because they showed efficient performance \cite{103}. RFECV \cite{92} selects the best subset of features by removing some features and selecting the best subset based on a cross-validation score. SMOTE \cite{103} adds synthetic data points by selecting random samples of the minority class and choosing a point in between these points and one of their k-nearest neighbors. We evaluated those models using different evaluation metrics such as Accuracy, F-measure, precision, recall, and AUC.

5.1. Datasets

Tables 12 and 13 show the characteristics of the datasets and their corresponding features used to evaluate our proposed system respectively: 1) PIMA India \cite{98} from the National Institute of Diabetes and Digestive and Kidney Diseases, 2) Sylhet \cite{99} was collected using direct questionnaires from the patients of Sylhet Diabetes Hospital in Sylhet, Bangladesh, and 3) MIMIC III \cite{100}, a large dataset which contains information of over 40,000 patients who stayed in critical care units of the Berth Israel Deaconess Medical Center between 2001 and 2012.

Table 12: Original Datasets Characteristics.

| Dataset   | # of Features | Positive Classes | Negative Classes | Total Records |
|-----------|---------------|------------------|------------------|---------------|
| PIMA Indian | 8             | 268 (34.9%)      | 500 (65.1%)      | 768           |
| Sylhet    | 16            | 320 (61.5%)      | 200 (38.5%)      | 520           |
| MIMIC III | 4             | N/A              | N/A              | 46,520        |

Table 13: Features of Datasets under Experiment.

| Sylhet     | PIMA Indian  | MIMIC III      |
|------------|--------------|----------------|
| Age        | Pregnancies  | Ethnicity      |
| Gender     | Glucose      | Gender         |
| Polyuria¹  | Blood Pressure| Age           |
| Polydipsia² | Skin Thickness| Family History of Diabetes |
| sudden weight loss | Insulin | |
| weakness | BMI           |                |
| Polyphagia³ | Diabetes pedigree* | |
| Genital thrush³ | Age |                |
| visual blurring |     |                |
| Itching    |               |                |
| Irritability|              |                |
| delayed healing |       |                |
| partial paresis⁵ |       |                |
| muscle stiffness |       |                |
| Alopecia¹  |               |                |
| Obesity    |               |                |

¹Polyuria is a condition where the body urinates more than usual and passes excessive or abnormally large amounts of urine each time you urinate \cite{99}.
Figure 8: Data Exploration Histograms for PIMA Indian Dataset Numerical Features.

5.2. Data Exploration

PIMA Indian dataset shows a number of missing values in some numerical features. In particular, Blood Pressure, Skin Thickness, and BMI are characterized by a heavy weight for the 'zero' value, on, shown in Figure 8. This implies that the corresponding observations should be removed at the preprocessing stage.

For each dataset, we study the correlations among features and the diabetic/non-diabetic class. We choose the Phik (Φk) correlation coefficient because that works consistently between categorical, ordinal, and interval variables. It captures non-linear dependency and reverts to the Pearson correlation coefficient in case of bi-variate normal input distribution [104]. So, it encompasses multiple types of correlations. As shown in Figure 9a, PIMA India presents a logical correlation between Age and Number of Pregnancies. Regarding diabetes detection, the features that are correlated with the diabetic/non-diabetic outcome of the patient are Glucose, Age, BMI, Insulin, and Skin Thickness. In addition, BMI is correlated with Blood Pressure. Correlations for Sylhet are displayed in Figure 9b. In this dataset, the diabetic/non-diabetic outcome is highly correlated with Polydipsia and Polyuria and in a lower manner with partial paresis, Gender, and sudden weight loss. Furthermore, Polydipsia and Polyuria are highly correlated with each other. Similar to PIMA India, MIMIC III
dataset shows high correlations between the class (diabetic/non-diabetic) outcome and the Age feature (Figure 9c). However, Figure 9c shows a correlation between Age and Ethnicity that may indicate the randomness in the MIMIC III dataset under study.

5.3. Data Preprocessing

In PIMA Indian dataset we remove observations with missing data for Skin Thickness, BMI, and Blood Pressure. Sylhet dataset does not have any missing value. Regarding MIMIC III dataset, there is a need to extract the available risk factor feature out of the raw data. MIMIC III raw data are split into different tables. The data of interest in MIMIC III for bringing out risk factors and diabetic/non-diabetic class is shown in Table 14.

Table 14: Data Tables used from MIMIC III Dataset.

| Table Name            | Available data and purpose                                      |
|-----------------------|-----------------------------------------------------------------|
| PATIENTS              | Subject ID, Gender, Date of Birth                               |
| ADMISSIONS            | Subject ID, visits of patient, start and end of the patient visit, other demographic data (Ethnicity) |
| DIAGNOSES_ICD         | Subject ID, Association of ICD9 diagnostics with patients       |
| ICD_DIAGNOSES         | Dictionary of ICD9 codes associated with their description      |

We build MIMIC III machine learning dataset by joining information of the patients from the different data tables (Table 14). For each patient, we have Age, and Ethnicity from PATIENTS and ADMISSIONS tables. The information about diabetic/non-diabetic outcomes is retrieved from the ICD9 diagnostics associated with the patient in table DIAGNOSES_ICD. If one of the diagnostics is for diabetes mellitus, then the patient is set to have diabetes. In the same manner, we create a feature ‘Family History of Diabetes’ by querying if a patient has ICD9 diagnostic code V180 (Family history of diabetes mellitus). The categorical values of ‘UNKNOWN/NOT SPECIFIED’, ’PATIENT DECLINED TO ANSWER’, ‘UNABLE TO OBTAIN’ for Ethnicity in MIMIC III dataset are interpreted as missing values. Consequently, patients with such values for Ethnicity are removed from the dataset. Table 15 shows the characteristics of the resulting datasets after preprocessing.

Table 15: Dataset Characteristics after Preprocessing.

| Dataset        | # of Features | Positive Classes | Negative Classes | Total Records |
|----------------|---------------|------------------|------------------|---------------|
| PIMA Indian    | 8             | 177 (33.3%)      | 355 (66.7%)      | 532           |
| Sylhet         | 16            | 320 (61.5%)      | 200 (38.5%)      | 520           |
| MIMIC III      | 4             | 8,820 (22.5%)    | 30,469 (77.5%)   | 39,289        |

5.4. Feature Selection

We use RFECV [92] with Random Forest [94] as cross-validation evaluator. Random Forest model is used to detect feature importance in learning. Random Forest is a kind of a Bagging Algorithm that aggregates a specified number of decision trees. The tree-based random forest ranks the features according to how well the purity of the feature is improved, that is, a decrease in the impurity (Gini impurity) over all the trees. Features with the greatest decrease in impurity happen at the start of the trees, while features with the least decrease in impurity occur at the end of trees. Therefore, pruning trees below a particular feature, one can create a subset of the most important features. Recursive
Figure 9: Correlation between Features and Diabetic/Non-diabetic Class for PIMA Indian, Sylhet, and MIMIC III Datasets
Feature Elimination works by searching for a subset of features by starting with all features in the training dataset and successfully removing features until the desired number remains. This is achieved by fitting random forest, ranking features by importance, discarding the least important features, and re-fitting the model. This process is repeated until a specified number of features remains.

5.5. Balancing Data Augmentation

The three datasets that we are using are slightly imbalanced towards the negative class, MIMIC III is more imbalanced. The number of diabetes class observations is roughly 30% for PIMA Indian and Sylhet datasets and 22% for MIMIC. To reduce the biases in the created models, the synthetic minority oversampling technique (SMOTE) [103] is used as data balancing technique. SMOTE is an oversampling technique that increases the number of minority class samples in the dataset, by generating new samples from existing minority class samples. The application of SMOTE to clinical datasets can improve model performance by reducing the negative effects of imbalanced data as observed in recent literature. SMOTE is only applied on the training/validation split (70%) of the data samples so that the model sees equal numbers of both class types, and the test split (30%) is not modified.

5.6. Machine Learning Models for Diabetes Prediction

We implement our proposed automated end-to-end blockchain AI-system for diabetes prediction using the most popular and accurate Random Forest (RF) model. Figure 10 shows the relative usage frequency of different Machine Learning algorithms in current research papers on Diabetes prediction [7, 8, 9, 10, 11, 12, 13, 14]. To evaluate our proposed system, we implemented Logistic Regression (LR) and Support Vector Machine (SVM) algorithms for diabetes prediction and compare their performances with RF. The selection of LR and SVM is based on their popularity as shown in Figure 10.

5.6.1. Random Forest (RF)

This algorithm is based on Decision Tree (DT), which constructs a tree structure to define the sequences of decisions and outcomes, and to use it for prediction. At each node of the tree, the algorithm selects the branch having the maximum information gain.

Random Forest is a set of decision trees constructed using randomly selected samples of the dataset [94]. It performs voting on the output of each decision tree and classifies an observation into diabetes or non-diabetes depending on the majority of the decision trees’ output.

5.6.2. Logistic Regression (LR)

This algorithm predicts the probability that a given observation belongs to diabetes or non-diabetes class using a sigmoid function [101] as stated in Equation 1.

\[
P_{\text{diabetes}} = \frac{e^{\beta_0 + \sum_{i=1}^{n} \beta_i R_i}}{1 + e^{\beta_0 + \sum_{i=1}^{n} \beta_i R_i}}
\]  (1)
where \( p(\text{diabetes}) \) represents the probability of having diabetes, \( R \) is the set of risk factors, and \( \beta_0 \) and \( \beta_i \) are the regression coefficients representing the intercept and the slope respectively. The values of regression coefficients are calculated using maximum likelihood estimation such that the value of Equation 2 is the maximum.

\[
\ell(\beta_0, \ldots, \beta_i) = \prod_{i,y_i=1} P(\text{diabetes}) \prod_{i,y_i=0} (1 - P(\text{diabetes})) 
\]

(2)

5.6.3. Support Vector Machine (SVM)

This algorithm aims to create a decision boundary known as a hyperplane that can separate n-dimensional instance space into diabetes and non-diabetes classes. The hyperplane is created using the extreme points (support vectors) of the dataset. The generation of hyperplane is an iterative process to find the maximum possible margin between the support vectors of the opposite classes, represent the risk factors and classes in the dataset and there exists a hyperplane that separates diabetes and non-diabetes classes. Let \( r^{(i)} \) and \( y^{(i)} \) represent the risk factors and classes in the dataset and there exists a hyperplane that separates diabetes and non-diabetes classes as stated in Equation 3.

\[
w^T r + b = 0
\]

\[
w^T r^{(i)} + b > 0, \text{ if } y^{(i)} = +1 \text{ and } w^T r^{(i)} + b < 0, \text{ if } y^{(i)} = -1
\]

(3)

where \( w \) is the normal of the hyperplane and \( b \) is the bias. The minimization problem
to obtain the optimal hyperplane that maximizes the margin can be formulated using:

\[
\text{Minimize} \Phi(W) = \frac{1}{2} ||W||^2, \text{ such that } y_i(W \cdot r_i + b) \geq 1
\]  \hspace{1cm} (4)

6. Performance Evaluation

For experiments, we use the three models we have selected as being mostly used in the context of Diabetes prediction, that is Random Forest (RF), Logistic Regression (LR) and Support Vector Machine (SVM). We will do the experiments with and without Feature Selection, and with and without balancing.

We evaluate the models under study with and without features selection, before and after balancing, using the tenfold cross-validation method where the dataset is divided into k (k=10) partitions. One partition is for testing data and k-1 partitions for training with replacement. This is repeated until each partition is used for training and testing. The resultant model is then obtained by averaging the result of each iteration. For SVM, we use the polynomial kernels. Each model is executed 10 times on each dataset and the average for accuracy, F-measure, precision, recall, AUC, and execution time is calculated. The use of Accuracy as a comparative metric between the models is justified because the datasets are not heavily imbalanced. The accuracy, F-measure, recall, and precision are calculated using Equations 5 and 6 respectively. Recall and precision for the positive (negative) class are calculated using Equations 7 and 8 respectively.

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}
\] \hspace{1cm} (5)

\[
F - \text{measure} = \frac{2(\text{Recall} \times \text{Precision})}{\text{Recall} + \text{Precision}}
\] \hspace{1cm} (6)

\[
\text{Recall} = \frac{TP(TN)}{TP(TN) + FN(FP)}
\] \hspace{1cm} (7)

\[
\text{Precision} = \frac{TP(TN)}{TP(TN) + FP(FN)}
\] \hspace{1cm} (8)

where TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative. TP (TN) represents the number of observations in the positive (negative) class that are classified as positive (negative), and FP (FN) represents the number of observations in the negative (positive) class that are classified as positive (negative).

We also calculate AUC. The Area Under the Curve (AUC) is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve. The higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes.
6.1. Hyperparameter Tuning

To achieve the best performance possible with the end-to-end system for diabetes prediction, we also perform fine parameter tuning with the best algorithm we have selected. We perform Hyperparameter tuning on the three AI models for the three datasets. Hyperparameter tuning relies on experimental results and thus the best method to determine the optimal settings is to try many different combinations and evaluate the performance of each model. However, evaluating each model only on the training set can lead to overfitting. To reduce the effect of overfitting we perform again stratified k-fold Cross Validation with k =10. The parameters we will study for each algorithm and their range are described in Table 16. To perform the search for best parameters, we use GridSearchCV from python library sklearn.model_selection module. Table 17 show the optimal values of hyperparameters obtained for the algorithms after parameter tuning.

Table 16: Value(s) of Hyperparameters used in Literature and in our Experiments for the Algorithms under study.

| Algorithm          | Hyperparameters | Value(s) used in the literature | Value(s) used in our experiments | Combinations used in our experiments |
|--------------------|-----------------|---------------------------------|----------------------------------|--------------------------------------|
| Random Forest      | Number of estima-tors/trees | 100 [7, 100, 300, 500, 1000 [13], and NR [8, 9, 10, 11, 12, 13] | 10, 20, 40, 60, 80, 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000 | 360 |
|                    | Maximum depth   | NR [7, 10, 11, 12, 13] | None, 2, 5, 8 |
|                    | Splitting criteria | NR [7, 10, 11, 12, 13] | Gini and entropy |
|                    | Maximum features | NR [7, 10, 11, 12, 13] | Nmax**, sqrt, and log2 |
| Support Vector Machine | Kernel | Linear [13, NR [7, 10, 11, 12, 13]] | Linear* | 26 |
|                    | Regularization parameter | (0.001, 0.01, 0.1, 1, 2, 3, 5, 7, 10) [13] and NR [7, 10, 11, 12, 13] | (0.001, 0.01, 0.1, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10) | 35 |
|                    | Kernel coefficient | NR [7, 10, 11, 12, 13] | 2^{-6}, 2^{-4}, 2^{-2}, 2^{0}, and 2^{2} |
| Logistic Regression | Regularization parameter | NR [7, 10, 11, 12, 13] | 2^{-6}, 2^{-4}, 2^{-2}, 2^{0}, 2^{2}, 2^{4}, and 2^{6} |
|                    | Solver | NR [7, 10, 11, 12, 13] | Newton-cg, lbfgs, liblinear, sag, and saga |
|                    | Maximum iterations | NR [7, 10, 11, 12, 13] | 3000 |

NR: Not Reported; * Radial Basis Function is not considered because the model does not converge with datasets containing thousands of observations; ** Nmax: number of features of the data; Newton-cg: Newton Conjugate Gradient
Table 17: Optimal Values for Hyperparameters Obtained in our Experiments.

| Algorithm          | Hyperparameters   | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|--------------------|-------------------|---|---|---|---|---|---|---|---|---|----|----|----|
|                    | Number of         | 50| 40| 50| 50| 20| 100| 50| 50| 20| 100| 50| 50 |
| Random Forest      | estimators/trees  |    |   |   |   |    |     |    |   |    |    |    |    |
|                    | Splitting criteria| entropy | entropy | entropy | entropy | Gini | Gini | Gini | Gini | entropy | Gini | Gini | entropy |
|                    | Maximum features  | None | sqrt | sqrt | log2 | sqrt | sqrt | sqrt | sqrt | sqrt | sqrt | sqrt | sqrt |
|                    | Max Depth         | 5   | 5   | None | 8   | None | None | None | None | None | None | None | None |
| Support Vector     | Regularization parameter | 1 | 1 | 1 | 7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Machine            |                   |     |     |     |     |     |     |     |     |     |     |     |     |
| Logistic Regression| Regularization parameter | 16 | 16 | 0.25 | 4 | 16 | 4 | 4 | 4 | 16 | 4 | 4 | 4 |
|                    | Solver            | lbfgs | lbfgs | lbfgs | lbfgs | lbfgs | lbfgs | lbfgs | lbfgs | lbfgs | lbfgs | lbfgs |

1 - PIMA Indian: no feature selection and no balancing, 2 - PIMA Indian colon feature selection and no balancing, 3 - PIMA Indian: feature selection and balancing, 4 - PIMA Indian: no feature selection and balancing, 5 - Sylhet: no feature selection and no balancing, 6 - Sylhet: feature selection and no balancing, 7 - Sylhet: feature selection and balancing, 8 - Sylhet: no feature selection and balancing, 9 - MIMIC III: no feature selection and no balancing, 10 - MIMIC III: feature selection and no balancing, 11 - MIMIC III: feature selection and balancing, 12 - MIMIC III: no feature selection and balancing.
6.2. Feature Selection

Following the feature selection method described in 5.4, we give the results for the three datasets.

For PIMA Indian dataset, there are 5 selected features: glucose, BMI, insulin, age, and diabetes pedigree function (Figure 11a). Figure 11b shows the importance of each feature to prediction. It shows that glucose is the most important feature in the prevalence/incidence of diabetes in users, followed by BMI, age, and diabetes pedigree function. This is confirmed by studies in literature [105, 106] and type 2 diabetes risk assessment form by the Finnish Diabetes Association [107].

For Sylhet dataset, there are 8 selected features: polyuria, polydipsia, age, gender, partial paresis, irritability, sudden weight loss, and polyphagia (Figure 12a). Figure 12b shows the importance of each feature to prediction. It shows that polyuria and polydipsia are the most important features in the prevalence/incidence of diabetes in users. This is in alignment with the result obtained in the literature [108]. In context of gender, figure reveals that men are more correlated with the prevalence/incidence of diabetes. This is confirmed by the American Diabetes Association’s type 2 diabetes risk test [109].

In the MIMIC III dataset, there are 4 attributes which all related to diabetes risk factors: gender, age, ethnicity, and family history of diabetes. The data preparation stage transforms the categorical feature Ethnicity into several binary features which explain the 'ETHNICITY_xx' feature names. Figure 13a shows that two features are selected as significant. The feature importance Graph Figure 13b shows that age has the highest importance for the prevalence/incidence of type 2 diabetes in the population. This is in alignment with the American Diabetes Association’s type 2 diabetes risk test [109]. The second important feature is the ethnicity of Black/African American. This is also confirmed by studies in literature [110, 111, 112]. Furthermore, Gender feature has low importance and consequently it was not selected.
Figure 12: Performance of Feature Selection Algorithms for Sylhet Dataset.

Figure 13: Performance of Feature Selection Algorithms for MIMIC III Dataset.
6.3. Hardware and Execution Time

The Hardware used for the performance analysis is Intel(R) Core (TM) i7-9700, with 32 Kilobytes L1 Data-cache, 32 Kilobytes L1 Instruction-cache, 256 Kilobytes L2 Cache, 12 Megabytes L3 Cache. The total execution times of each machine learning model under study for PIMA Indian, Sylhet, and MIMIC III datasets are shown in Figures 14a, 14b, and 14c respectively. The measurements has been done using the tuned parameters for each model. It consists of the total time for training and validating the model. We can observe that Random Forest (RF) uses more CPU. The main reason is that number of estimators (n_estimator) is the principal parameter driving computational usage.

6.4. Experimental Results Analysis

In this section, we analyze our experimental results and give insights into the reasons for the obtained performance. To compare the different metrics for the models under study Figures 15, 16, and 17 shows the Accuracy, AUC, Recall, Precision, and F-measure values of the models for the different datasets, with and without feature selection before and after balancing. From the raw results of accuracy we can see that feature selection improves or at least does not degrade accuracy. As for balancing, we observe that mixed results on accuracy depending on how balanced were the data initially. Accuracy is improved with data balancing in the case of RF algorithm where we can see an increase of accuracy from 0.77 to 0.81 for PIMA Indian, 0.97 to 0.98 for Sylhet. For MIMIC III dataset, accuracy decreases from 0.77 to 0.66 with data balancing, but the F-measure increases from 0.51 to 0.66. This is a general conclusion for all datasets and all algorithms, analysis of confusion matrices can give an insight on this . The confusion matrices (figures 18, 19, and 20) before and after feature selection and balancing, we can see that after balancing there is a better detection of the minority class. For the RF algorithm the increase in detection of the minority class is 70% less false negative for PIMA Indian and 80% less false negative for MIMIC III dataset. For Sylhet dataset there is no significant improvement because it is already balanced and there was no false negative before balancing.
Figure 15: Comparison of Accuracy, F-measure, Recall, Precision, and AUC for the algorithms under study on PIMA Indian dataset (FS: Feature Selection, BL: Data Balancing).
Figure 16: Comparison of Accuracy, F-measure, Recall, Precision, and AUC for the algorithms under study on Sylhet dataset (FS: Feature Selection, BL : Data Balancing).
Figure 17: Comparison of Accuracy, F-measure, Recall, Precision, and AUC for the algorithms under study on MIMIC III dataset (FS: Feature Selection, BL : Data Balancing).
Figure 18: Confusion Matrices for PIMA Indian dataset.
Figure 19: Confusion Matrices for Sylhet dataset.
Figure 20: Confusion Matrices for MIMIC III dataset.
The execution times of the algorithms for the PIMA India and Sylhet are negligible while, for the MIMIC III are the highest. This is because time is a function of the number of features and observations. The datasets we used are not heavily imbalanced, so we can notice that balancing does not show accrued accuracy (exception for Sylhet dataset where there is a slight improvement). This is particularly true for MIMIC III dataset, because it does not present enough risk factor features and it is also the most unbalanced. The balancing algorithm (SMOTE) is inefficient in producing a better training in this case, this is because SMOTE oversamples uninformative samples. As a general result we can observe that feature selection that we perform in the system does not degrade the accuracy and can reduce the processing time. The Best ML algorithm for PIMA Indian dataset us Random Forest when using Feature Selection with an accuracy score of 0.7827. The Best ML algorithm for Sylhet is Random Forest with accuracy score of 0.9723, the feature selection brings a slight decrease in processing time and the accuracy does not suffer. The best ML algorithm for MIMIC III dataset is Logistic Regression, but Random Forest is very near. Best accuracy for LR 0.7734 and best for RF 0.7703 and difference of only 0.4%. ROC curve analysis show that Sylhet dataset, the Random Forest classifier is very good. The results for Sylhet dataset are exceedingly better than for PIMA Indian and even more than for MIMIC III. The main difference between these datasets is the number of available features that can be seen as Risk Factor for diabetes. In conclusion, we can say that we should strive to get data with as many risk factors as possible (i.e. Sylhet dataset. The dataset we used for analysis were not diverse enough to assess the need or balancing the data. The use Random Forest with feature selection is justified in the system, as it can reduce processing time.

7. Conclusions

In this paper, we propose an end-to-end integrated IoT-edge-AI-blockchain monitoring system for diabetes prediction. In addition, we evaluate machine learning algorithms within the proposed system using three diabetes datasets in a unified setup and compare their performance in terms of accuracy, F-measure, and execution time. Our experimental results show that the RF is the most accurate. Additionally, we classify type 2 diabetes risk factors to analyze the most significant properties for diabetes prediction. When using a classification algorithm for the prediction of type 2 diabetes, the following requirements should be considered.

1. **Accuracy vs F-measure**: Most of the algorithms give a high classification accuracy. However, evaluating the classifier performance using only the accuracy can be misleading. This is because, in the case of an imbalanced dataset, which is very frequent in the health domain, the algorithm might have high accuracy but will not be able to classify the minority class labels as revealed by the F-measure. In such a situation, the prediction results can lead to a life-threatening situation, as a diabetic patient can be classified as non-diabetic. Consequently, we recommend the data scientist include F-measure as one of the evaluation metrics.

2. **Feature selection**: Feature selection algorithms should be used on the dataset before training the classification model. This can avoid overfitting and reduces execution time.
The experiment we conducted show that feature selection does not incur accuracy degradation.

3. **Significant features:** As a recommendation we can propose to use age, ethnicity, glucose, family history of diabetes, and obesity for prediction of type 2 diabetes based on our experimental results. This is in alignment with the Finnish Diabetes Association’s type 2 diabetes risk assessment form [107] and the American Diabetes Association’s type 2 diabetes risk test [109].

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**Declarations of Interest**

Declarations of interest: none

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