# Cloud-Based Diabetic Prediction Framework: Deep Learning Approach

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***Abstract*— Since Diabetic is one of most common growing disease in the world. Which open the gate for another kind of diseases such as blindness, kidney problems, heart disease and more. Therefore, we need to develop a system the predict diabetic before it happens to people and advise them to avoid it. The system is more than early detection as its prediction. We propose a cloud-based secure framework that integrates traditional machine learning methods with deep neural networks. The system collect patients readings using IoT devices and sensors, where it will be moved securely using public key encryption to cloud storage. Then the prediction algorithm perform on time prediction on the data to see if the patient expected to be diabetic in the future or not. The prediction techniques tested on Pima Indian diabetic dataset from UCI. The result shows that it performs traditional ML methods with accuracy of 98%.**

***Keywords— E-Health, deep learning, Deep neural network, machine learning, diabetic prediction, diabetic prediction, IoT***

## I. Introduction

The proliferation of new technologies and smart devices facilitate the human life, and decrease the human effort, which results in increasing the risk factors for developing diseases such as high blood pressure, and diabetic. The number of patients in diabetic is expected to reach 625 million by 2045[1].

Diabetes is a chronic common disease that affect the health of the entre people in the earth. It destabilizes the sugar level in the blood. The normal range of sugar in the blood is from 70 – 180mg/dl. There are number of different diabetic and the most common are type 1 and 2. Type 1 diabetes appears in children and type 2 diabetes for the middle aged and old people[2]. Diabetic open the body for other disease such as kidney problems, heart disease, nerve problem and disabilities[3]. Diabetic become a major health problem. The traditional way of sugar level Self-monitoring is finger stick samples[4]. Modern devices invented to control the sugar level that record the patient state every mints such as using electromagnetic radiation[5]. With the emerging of IoT and e-health framework, patient monitored remotely and regularly. Health organizations concentrate their attention to use the new technologies and artificial techniques in diagnosing and predicting the probability of diabetes occurrence, as it has undesired effects when it does not discover and treat in the first stages. Diabetes Mellitus (DM) is a long-time term disease problem, which has an inverse impact on the human social life

Huge research carried out to apply the internet of things (IoT) in what smart healthcare. It helps doctors to diagnose patients without direct contact. It can be done by analyzing hug amount of patient data collected by IoT devices; this will reduce the time and protect medical staff from infection. IoT is a collection of connected objects that employ technology and algorithms on data to develop solutions or services for smart applications[6]. The integration IoT with Artificial intelligent and cloud computing gives and advantage to all environments[7], mainly the health sector. It will reduce the cost and protect doctors and nurses from infectious diseases. It could be used to give an initial prediction for their illness, and send an alarm in case or critical situation[8]. While previous data helps to diagnose patient and prescribe medicine and suitable treatment. All kind of reading can be collected such as heart rate, EEG, blood pressure, temperature, glucose level, x-rays, depression, mood and other readings. Usually data can be collected using microcontroller such as raspberry pie and Arduino, then stored in the cloud for analysis[9]. Data processed on the cloud or fog computing for real-time response. Security need more attention here where data travel through the internet[10]. However, all using smart health care system is moving to the cloud technology faster than before[11, 12]. For example; a personal health dashboard that use cloud-based system developed to monitor patients, analyses their data and detect COVID-19[13, 14]. Such a system must be deployed with high level of security to protect patient's information.

The focus of smart healthcare is to measure vital parameters of human body: temperature, Pulse rate, Respiration rate, Oxygen level and Blood pressure. Vital signs are useful in detecting or monitoring patient's health. Other useful parameters can be measured such as gesture, facial expression, Consciousness level and body language. Remote monitoring systems developed to measure PPG, EGC and temperature to check the patient status[15-17], most of them are using chair to measure these vitals such as car seat, wheelchair or smart chairs. Wearable devices developed over years to measures temperature and other vital sign[18-20]. Currently smart mobile devices has the ability to measure vital signs. Mobile health (m-health) uses mobile devices to collect real time data and store it a server[21, 22], the collected data can be analyzed and processed using AI to give initial diagnose. M-health reduces the costs and improve the quality of healthcare, but it comes with challenges in terms of interoperability and security [4, 22]. More research done to develop a secure framework for m-health the focus on authentication and Encryption[23-25]. Any remote healthcare system has more benefits and great transformation to healthcare, but raises a security challenges. Security and privacy become more important in healthcare. Attackers can use any methods to find out sensitive data and release it to the public[26]. A secure framework must be used to prevent leak of information and threats to patients. Data transmitted over internet should be encrypted to insure integrity and privacy of the patient. A combination of PKI, Smartcard and Biometrics technologies developed to secure the clinical data[27], it is a multi-layered healthcare framework depends on public key and physical protection.

Doctors and health organization may depend on m-health or smart house to monitor and track their patients. Smart house uses a network of sensors to record vital signs and monitor patient as it is in the hospitals[28, 29]. Raspberry Pie device used to measure vital health signs for home patient and send it to doctors at hospitals[26, 30], where family and patient himself can see his status and prescription from doctors. The collected data can be used to predict the sickness level using data mining techniques[31]. In addition, predict the future health conditions of the patients[32]; such as diabetic prediction[33] and heart disease prediction[33]. Unpublished review on health monitoring using Smart Home[34] explored the use of IoT in healthcare and conclude that a good collaboration and unified technology must be used to have a complete reliable smart home for healthcare monitoring. The health care transformation will make a cloud based secured framework where patients' information can be securely transferred by having a network between patient, hospital, doctors, and Labs. Where data can be accessed securely from anywhere at any time. The main benefits of that is reduce the cost on patient, a unified copy of patient record and deal with lack of specialist and doctors.

In this paper, we propose a secure cloud based diabetic prediction framework. We test the prediction techniques on existing diabetic dataset and compare it with traditional machine learning methods.

## II. Related work

The World Health Organization (WHO) states that the number of deaths in diabetes patients is increasing exponentially as it was increased by 70% during the interval 2000 to 2019 in all over the world, and diabetes results in the death for more than 1.5 million individuals per year[35]. The technology used more in diabetes treatment as it includes set of hardware devices and software tools. These tools enable the diabetes' patients to manage monitor the blood glucose levels, and the use of historical diabetes technology which is divided into two main branches: insulin management by using syringe, pen, or pump, and blood glucose monitoring through using glucose monitor[36]. Artificial Intelligence (AI) is used to enhance the medical diabetes treatment and to enhance the prediction of diagnosing diabetes' patients[37].

There are several contribution on diabetic prediction and detection techniques. Machine learning development increased with the new computer technology by improving data analysis and train the computer applications to diagnose diseases using supervised learning algorithm and evaluate it using test data[38]. Detecting diabetic techniques contains many processes starting from data collection, data cleaning, feature extraction and selection, classifications and predictions. Many ML methods applied on different data structure.

The development of AI techniques contributes to develop accurate models that used to recognize diabetes mellitus patients and the probability of occurrence. Several machine learning algorithms suggested predicting diabetes mellitus, these algorithms based on supervised learning, hybrid learning, or even ensemble learning[39].

Classification algorithms integrated with clustering approach to enhance the accuracy of classification by adapting the feature selection approach[40]. The proposed approach divided into three stages: firstly, feature selection as it is noted that the clear feature selection led to improvement in classification's accuracy. Secondly, clustering by implementing K-means and hierarchical clustering of group datasets, and finally classification is done by adapting naive Bayes classifiers. Different algorithms implemented to enhance the accuracy of diabetes mellitus diagnosing[41]. It shows that soft voting classifier achieved 79.08 % accuracy when it compared to the other existing machine-learning algorithms. ML algorithms implemented in in healthcare using predictive analytics through using six different algorithms with a dataset of patient's medical record[42], where KNN and SVM are superior to the other tested algorithms with accuracy reached to 77%.However, the size of the dataset and number the missing values is a limitation. Artificial Neural Network (ANN) prediction model proposed to recognize diabetes mellitus[43], dataset is collected from Kurdistan region by gathering information from pregnant women with and without diabetes. The proposed model enhances the prediction accuracy to reach 91% depending on the network design. Bansal, Diabetic analyses model developed using K-means clustering with support vector machine (SVM)[44]. It used Pima Indian diabetic dataset (PID). The model was effective but the efficacy evaluated based on exploratory studies. Adaptive neuro-fuzzy inference system (ANFIS) for early diagnose of diabetic[45] used intelligent techniques. But developed to reduce the data's characteristics. Diabetic analysis has been studied using variety of machine learning methods such SVM, decision tree, naïve Bayes, and other methods, but most of these studies used collected data from hospitals and the correctness depends on how clean is the data[46]. A comparison on six ML methods on the same data set shows that SVM and KNN have better accuracy[47]. Another study shows that random forest is best [48]. The performance of the machine learning algorithms for the prediction of diabetes evaluated[49]. The evaluation on support vector machine, artificial neural network, logistic regression, classification tree, and K-nearest neighbour. Logistic regression got the highest accuracy 78%. The accuracy of artificial neural network was the best in another evaluation of ML methods[50]. A comprehensive review of ML diabetics prediction models done lately [51] has reduced the conflict by previous studies on which method has the best accuracy by browsing the datasets conditions and what affect the method performance.

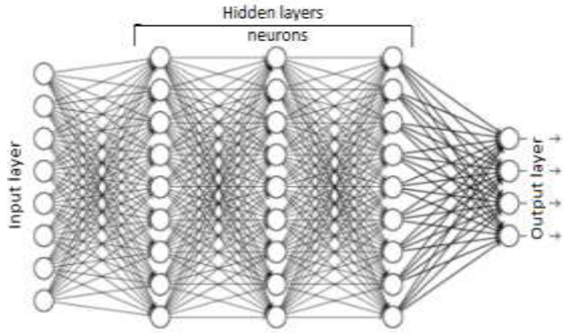


**Fig. 1**. The architecture of deep neural network

The use of deep learning has grown faster because it simulate the human mind. They are used in different forms in the health field[52, 53] and proven to be the better by reducing error rate and robust against data noise[54, 55]. A deep neural network has hidden layers between the input and output layers. Its developed to predict by exploring the patterns in data set. The accuracy is much better when the techniques trained well. The architecture of deep neural network contains many hidden layers and several neurons in every hidden layer as shown in Figure 1.

## I. METHODOLOGY

The proposed framework contains four phase distributed over three layers as shown in Figure 2. The first phase is Data collection where data can be collected using smart devices and with the use of IoT technology. The second phase is data pre-processing where we clean up the data and remove unnecessary features. The third phase is the prediction phase where the implemented hybrid algorithm is used to analyses the collected data and draw a diabetic prediction using medical facts and historical records. The phase is the evaluation criteria. These phases distributed over three layers: sensor layer where IoT devices and sensors used to collect data, security layer where data will be encrypted using public key encryption, the last layer is the cloud layer where the computation will take place.

The collection layer will employ IoT devices to collect patient's data with. Sensor devices can be wearable, embedded in the body, on Apps on smart devices. The communication technology on the sensor device will enable it to transfer the data to a health gateway, which in turn forward these accumulated data to cloud storage. The data will be encrypted using patient private key before transmitting it to cloud. There are two operations for the security process:

Key management: RSA algorithm will be used to generate pair of keys for each patients and specialist. The public key will be stored in a directory on the cloud and used to encrypt and decrypt data to/from patient gateway/specialist. In addition, give access to authorized users to access patient records.

Data encryption/decryption: patient data will be encrypted using his own private key, and decrypted using his public keys. Request to access data encrypted using requester private keys and replies encrypted using requester public key.

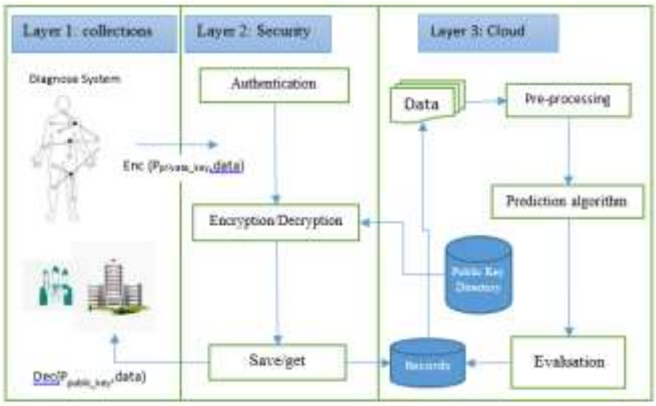


**Fig. 2**. Proposed framework

The cloud layer will employ deep learning techniques to analysis the data predict diabetic for current patient in the future. Healthcare specialist and organization to view patient records in a secure channel based on access privileges. The main focus of this paper is on the accuracy of diabetic prediction and the security layer will be discussed in future work.

## II. DATASET

The framework depends on real time data collected by IoT in time. Sense we have not implement this in reality, we will use a common used data set for prediction of diabetes is the Pima Indian Diabetes dataset is retrieved from the UCI machine learning repository database[56]. The data set contains of 768 rows and 9 columns. The attributes are glucose, pregnancies, skin thickness, blood pressure, BMI, insulin, and age. The last column is test result: positive or negative for diabetic. Table 1 below the features and there properties.

**Table 1**. Dataset Features

| **Feature** | **Description** | **Type** |
|---|---|---|
| Preg | Number of times pregnant | Numeric |
| Gluc | Plasma glucose concentration at 2 Hours in an oral glucose tolerance test (GTIT) | Numeric |
| BP | Diastolic Blood Pressure (mm Hg) | Numeric |
| Skin | Triceps skin fold thickness (mm) | Numeric |
| Insulin | 2-Hour Serum insulin (µh/ml) | Numeric |
| BMI | Body mass index [weight in kg/(Height in m)] | Numeric |
| DPF | Diabetes pedigree function | Numeric |
| Age | Age (years) | Numeric |
| Outcome | Binary value indicating non-diabetic /diabetic | Factor |

## III. PROPOSED FRAMEWORK

The framework is design for real time analysis and data collected on time remotely over years to predict diabetic. Due some network disconnections or device faults (down), some readings could not reach the cloud storage. Therefore, pre-processing is an essential step to avoid in accurate prediction. The algorithm will consider the reading as a DNA for the person over time and any missing values will be replaced based on previous and current readings.

In this research, Pima data set to check the accuracy prediction. Therefore, we will focus on cleaning data and feature selection at this stage. We use python to check the data set for missing or none values. The test shows that the data has not missing or none values but some features values are inconsistent: glucose, blood pressure, skin fold thickness, insulin and BMI. This may affect the accuracy of the algorithm. If we look at the statistic of the data set as shown on table 2. We can see many zeros as all null values replaced by Zero. The real time dataset will not contain many zeros', because a genetic algorithm will replace missing values with a values base on previous and future value for this feature. However, the data set we used can be replace because we have no history and not on time data. Also, dropping one of eight features is not a good idea. It may reduce the noise but reduce the accuracy as well.

Table 2: Data set features statistics.

| | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|
| **Pregnancies** | 3.84505 | 3.36958 | 0.0 | 1.00 | 3.00 | 6.00 | 17.00 |
| **Glucose** | 120.89453 | 31.97262 | 0.0 | 99.00 | 117.00 | 140.25 | 199.00 |
| **Blood Pressure** | 69.10547 | 19.35581 | 0.0 | 62.00 | 72.00 | 80.00 | 122.00 |
| **Skin Thickness** | 20.53646 | 15.95222 | 0.0 | 0.00 | 23.00 | 32.00 | 99.00 |
| **Insulin** | 79.79948 | 115.24400 | 0.0 | 0.00 | 30.50 | 127.25 | 846.00 |
| **BMI** | 31.99258 | 7.88416 | 0.0 | 27.30 | 32.00 | 36.60 | 67.10 |
| **Diabetes Pedigree** | 0.47188 | 0.33133 | 0.078 | 0.24375 | 0.3725 | 0.62625 | 2.42000 |
| **Age** | 33.2 | 11.8 | 21.0 | 24.0 | 29.0 | 41.0 | 81.0 |
| **result** | 0.35 | 0.48 | 0.0 | 0.00 | 0.00 | 1.00 | 1.00 |

Table 3 shows the correlation between all variables. As we can see that some features have significant correlation with the outcome which are glucose levels, age, BMI and number of pregnancies. However, higher blood pressure is correlated with a person not being diabetic and Logistic Regression model confirm that blood pressure have negative impact on the outcome variable. however, combining blood pressure with other features will give positive impact on the accuracy.

Machine learning classifiers used on the dataset. Data split into two sets: training (90%) and test (%10). KNN, SVM and Random forest are supervised ML where .KNN is used to classify dataset's columns, SVM is suitable for small datasets and RF classifier is a several decision tree. The ML methods are used more like a feature selection techniques.

The prediction system implemented using python library. Deep neural network with 4 hidden layers is implemented and the number of neurons are 12, 16, 16 and 14 respectively for layer 1, 2, 3 and 4. The best performance for diabetic prediction of the algorithm on four layers architecture. The input layer layers are eight and the output is one. The output is one layer because the output can be inferred as positive or negative. To evaluate the supervised machine learning algorithms, the confusion matrix is used. Where it makes the evaluation of the accuracy is easy.

Table 3: Correlation between features

| | Pregnancies | Glucose | Blood Pressure | Skin Thickness | Insulin | BMI | Pedigree Function | Age | Outcome |
|---|---|---|---|---|---|---|---|---|---|
| **Pregnancies** | 1.000000 | 0.129459 | 0.141282 | -0.081672 | -0.073535 | 0.017683 | -0.033523 | 0.544341 | 0.221898 |
| **Glucose** | 0.129459 | 1.000000 | 0.152590 | 0.057328 | 0.331357 | 0.221071 | 0.137337 | 0.263514 | 0.466581 |
| **Blood Pressure** | 0.141282 | 0.152590 | 1.000000 | 0.207371 | 0.088933 | 0.281805 | 0.041265 | 0.239528 | 0.065068 |
| **Skin Thickness** | -0.081672 | 0.057328 | 0.207371 | 1.000000 | 0.436783 | 0.392573 | 0.183928 | -0.113970 | 0.074752 |
| **Insulin** | -0.073535 | 0.331357 | 0.088933 | 0.436783 | 1.000000 | 0.197859 | 0.185071 | -0.042163 | 0.130548 |
| **BMI** | 0.017683 | 0.221071 | 0.281805 | 0.392573 | 0.197859 | 1.000000 | 0.140647 | 0.036242 | 0.292695 |
| **Pedigree Function** | -0.033523 | 0.137337 | 0.041265 | 0.183928 | 0.185071 | 0.140647 | 1.000000 | 0.033561 | 0.173844 |
| **Age** | 0.544341 | 0.263514 | 0.239528 | -0.113970 | -0.042163 | 0.036242 | 0.033561 | 1.0 | 0.238356 |
| **Outcome** | 0.221898 | 0.466581 | 0.065068 | 0.074752 | 0.130548 | 0.292695 | 0.173844 | 0.238356 | 1.000000 |

## IV. Result and Analysis

The paper propose a diabetic prediction framework using Deep Neural network (DNN) integrated with traditional machine learning methods for feature selection. We have used a python open source library for machine learning called Scikit. The best performance of deep neural network in five-fold cross validation with accuracy 98.04, sensitivity 98.7, and F1 score equal to 0.99. Table 4 show the comparison between existed methods and the deep neural network approach.

**Table 4**. Comparison study of ML methods and DNN

| Method | Accuracy |
|---|---|
| SVM | 82.8 |
| GA | 80 |
| DNN | 98.4 |
| KNN | 76 |
| RF | 83 |
| Decision tree | 78 |
| LR | 78 |
| Naïve Bayes | 80 |

The prediction techniques applied on existing data set to compare its accuracy with existing methods. The best accuracy happen to be with the proposed DNN. The accuracy reached this limit because we get benefit from the traditional machine learning methods for classifications and feature selections. The correlation between features help us to decide which features are related to each other's and important for increasing the accuracy. However, accumulative reading may help us with the use of integrated DNN to predict the diabetic before it happen based on the patient readings over years. This accuracy will help us to distinguish real diabetic expectation from on time data analysis.

## V. Conclusion

Diabetic is a chronic disease that force people to live in different way from normal people. Otherwise, it may cause death or bring other diseases. Discovering diabetic in early stage is good for medical treatment. However, predicting it years before it happen is a way to avoid getting it and live normal life. This paper, implement diabetic prediction framework that has three layers where patients data collected and sent protected to a cloud storage, where it will be explored by integrated prediction system that combine traditional machine learning methods with deep neural network to predict diabetic. The proposed prediction method tested on Pima Indian diabetic dataset and shows best performance with 98% accuracy. The proposed framework will benefit individual who has historical diabetic in their family to track themselves and be aware of their diabetic early. Also, provide hospitals with early alarm to advice patients with early procedure to avoid complications.

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