International Journal of Scientific Research in Science and Technology
Print ISSN: 2395-6011 | Online ISSN: 2395-602X (www.ijsrst.com)
doi : https://doi.org/10.32628/IJSRST

An App for Health Monitoring for Diabetic Patient

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Article Info
Volume 9, Issue 3
Page Number : 168-174

Publication Issue
May-June-2022

Article History
Accepted : 08 May 2022
Published : 20 May 2022

ABSTRACT
The creation of multiple apps has been aided by the advancement of the digital era. The growing population has resulted in an increase in the number of persons suffering from a variety of diseases. Diabetes is one of the most common diseases that affects the majority of people around the world. It is vital for them to assess the level of glucose in their bodies using a variety of invasive procedures. Patients who use these methods experience a lot of pain. To avoid these techniques, we presented in this app that relies on the level of glucose in the body, user input, and daily health data. Android is used because it is faster and more efficient than other phones. Patients in rural places are unable to visit hospitals on a regular basis, and our app will help to alleviate this problem. The app is efficient and dependable because patient monitoring may be done anywhere. When compared to other traditional health monitoring systems for patients in hospitals, the system's Performance is evaluated and shown to be substantially more efficient. Regular blood glucose monitoring is important for decreasing and avoiding diabetic complications such as cardiovascular disease, hypertension, and cardiac strokes, among others. The proposed system keeps track of the users' numerous health-related behaviors. It can be thought of as a healthcare information platform that allows patients, medical institutions, and medical devices to communicate via data transmission. The machine learning algorithms assist the user in comprehending and reviewing their current health habits as well as predicting future health changes.
Keywords: Diabetes, diseases, Patients, health data, glucose

I. INTRODUCTION

Diabetes is a serious, complex metabolic disease for which a healthy diet and self-management system are essential. Diabetes treatment is complicated, and there are numerous factors to consider. Despite the fact that the internet is a growing source of information and resources, the average patient often lacks the skills to find and use the most up-to-date health-care information, and they may choose to forego treatment. Patient self-management is not just dependent on the patients themselves, but also on the provision of health care assistance encouraging patients to control their health. Diabetes is a difficult condition in which the body's ability to utilise and retain glucose is impaired (a form of sugar). Glucose produces an increase in blood glucose, also known as blood sugar, which has an impact on the patient's physical state.

High blood pressure is one of numerous risk factors that can raise the risk of getting heart disease, renal disease, stroke, and other complications. People nowadays lack the skills and willingness to adjust their lifestyles to better suit their health situations. There are several tools available to assist patients in taking an active role in their diabetes treatment while also improving their metabolic parameters. This suggested mobile application will make an attempt to make Diabetic sufferers' duties simpler.

The goal of this application is to provide patients with a well-balanced diet by coordinating the balancing of dietary energy. This programmer will provide the user with a food plan that is based on information from the Diabetic Patients' Book. Every time he consumes food, the user can add a food item to his list or replace any food items. The amount of food with the estimated food energy (Calorie, Carbohydrate, Protein, Fat) is provided with each food item, and if any of them exceeds the calculated marginal level of energy, the user will be notified that he has consumed more or less of that specific food energy.

This app has a medication alarm function. This function allows the user to set the time, name, and amount of medicine and get an alert at the specified time as a reminder. This application will also allow you to update your blood pressure and blood levels in daily bases. The user can enter diastolic and systolic pressures using this function. Blood sugar levels may also be tracked by inputting sugar levels before and after meals, as well as the time and date. This app includes the ability to make emergency calls and send messages. To reason the diabetic patient, a Multilayer Perceptron (MLP)-based classification algorithmic program is utilized, while Long memory (LSTM) is used to forecast the BG level.

II. RELATED WORK

Mai Ali [1] shows a unique framework for a remote-controlled glucose monitoring device implanted in the body. The RF signal's interaction with the biological tissue under study has been studied. An external unit powers the implanted device from a distance through inductive coupling. The design of two efficient class E Power Amplifiers (PAs) with power efficiency of 76 percent for the external power unit and 73 percent for the implanted unit is an original component of this work. The glucose data is sent from the implanted wireless transmitter to the patient's phone or PDA through Bluetooth low energy, a low-power communication protocol.

Ruhani Ab[2] describes a non-invasive breath test for diabetes patients to check their status. It has been found as a more straightforward method for diagnosing diabetic ketoacidosis (DKA). DKA is a type 1 diabetes mellitus complication that may be avoided. Urinary tests and blood ketone tests are two common diabetic tests performed on individuals to assess their diabetes state. Those procedures, on the other hand, are seen as intrusive, inconvenient, and expensive. Breath acetone has recently been proposed as a novel ketone biomarker since it is non-invasive, easy, and accurate in determining the body's ketone levels. This study shows how breath measurement may be used to monitor ketone levels. The main goal of this study is to propose a simple portable health care system for monitoring diabetes levels using breath. The method entails the creation of hardware that connects to an Internet of Things (IoT) system to aid in the diagnosis and monitoring of patients. The Arduino board is utilised in this setup to read the sensor and feel the breath. Wireless communication is used to log the breath value level to the system. The data gathering system is linked to a web page. The quantity of breath acetone collected when patients exhale into a mouthpiece with a gas sensor is used to determine the ketone level. The data from the Arduino is sent to the database through the ESP 8266 Wi-Fi Module, where it may be viewed by patients or physicians who have registered. This study is noteworthy because people may check their diabetes status autonomously, and the IoT system can warn medical personnel immediately officers in the hospitals.

Type 2 diabetes, which accounts for 90–95 percent of all diabetes occurrences [3], is a rapidly spreading epidemic that is taking a toll on health-care systems worldwide, particularly in developing countries. Because of the scale of the problem and the present epidemic of diabetes, finding novel techniques to better understand and treat the condition is a top concern. Gastrointestinal surgery might open up new avenues in the battle against diabetes. Traditional gastrointestinal surgeries for morbid obesity have been demonstrated to significantly improve type 2 diabetes, resulting in normal blood glucose and glycosylated hemoglobin levels and the cessation of all diabetic medications. Within days of surgery, euglycemia and normal insulin levels are observed, suggesting that weight loss alone cannot clearly describe why surgery improves diabetes. Recent experimental findings reveal that gastrointestinal architecture reorganisation is a main mediator of surgical diabetes management, implying a role for the small bowel in the disease's pathophysiology. The information presented in this article supports the hypothesis that type 2 diabetes is a treatable disease with a component of intestinal dysfunction.

Diabetes prevalence data for adults (age 20) were derived from studies which met the following criteria [4]: a defined, population-based sample, and diabetes diagnosis based on optimal WHO criteria (a venous plasma glucose concentration of >11.1 mmol/l 2 h after a 75-g glucose tolerance test). The exceptions to the latter criterion were a research in China [3], which employed a test meal, and a study in Tanzania[2], which found a greater incidence of diabetes using fasting glucose alone than a previous study using the ideal WHO criteria. Individual country prevalence estimates for type 1 diabetes for persons under the age of 20 were calculated using techniques specified in the International Diabetes Federation (IDF) Diabetes Atlas 2000 (6). Population-based data are not available for type 2 diabetes in people <20 years of age, and this group has been excluded from these estimates.

Diabetes case management is an approach that can give us with accurate information about diabetes patients [5.] The diabetic monitoring framework is critical for ensuring patient safety, especially when employing Internet-based devices (IoT). The framework can basically evaluate diabetic patients and store data including such blood sugar, internal temperature, and surface area. Part of the framework isn't just for assessing patients; it can also use artificial intelligence to organize the data. Patients are important because they can assist diabetics, their families, healthcare professionals, and clinical analysts in developing diabetic treatment programmes based on a variety of data. App that measures exposure and accuracy. It's all about recalculation, which is the polar opposite of selecting the greatest option under given constraints.

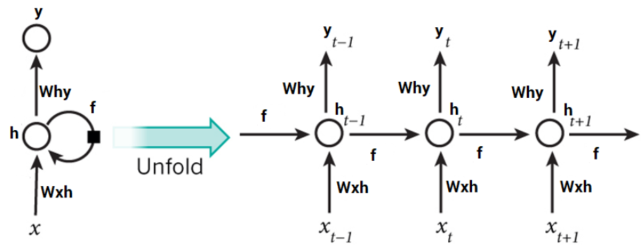
III. METHODOLOGY

2.1 RNN+LSTM (Convolutional Neural Network + Long Short-Term Memory)

The RNN Long Short-Term Memory Network, or RNN LSTM, is a type of LSTM architecture designed to improve accuracy of regression and clustering problems. Clustering analysis from of the RNN model is extracted, processed, and passed to the LSTM for prediction. Back in 1997, an improved way of back propagating the error provided the Long Short-Term Memory (LSTM) network an advantage over other recurrent networks. This was termed "constant error back propagation" by Hochreiter and Schmidhuber.

2.2 RNN (Recurrent Neural Network)

RNNs (recurrent neural networks) are a type of artificial neural network that can be used to model sequence data. RNNs that are derived from feed forward networks behave similarly to human brains. Simply put, recurrent neural networks can anticipate sequential data in a way that other algorithms can't. The information in a feed-forward neural network only flows in one way from the input layer to the output layer, passing via the hidden layers. The data travels in a straight line through the network, never passing through the same node twice. The data in an RNN cycles via a loop. When it makes a decision, it considers the current input and what it has learned from previous inputs. As a result, there are two inputs to an RNN: the present and the recent past. This is important because the data sequence contains critical information about what will happen next, which is why an RNN can perform tasks that other algorithms cannot. A short-term memory is present in a typical RNN. They also have a long-term memory when used in combination with an LSTM.



RNN Fundamental Diagram of Deep Learning

2.3 LSTM (Long Short-Term Memory)

Long Short Term Memory Networks (LSTM) are a sort of RNN that allows data to be stored. The vanishing gradient problem of RNNs, in which long-term dependencies are not remembered, is overcome with LSTMs. In LSTMs, gated cells are used to store data outside of the RNN's normal flow. Using these cells, the network may update the information in a number of ways, including storing and reading data. There are several similarities between both the LSTM and the RNN, despite the differences that make the LSTM a more powerful network. It keeps a record of one-to-one, many-to-one, one-to-many, and many-to-many input and output configurations. It is also possible to use a stacked configuration.

The forward propagation inside an LSTM cell may be seen in the image above. It is far more complicated than a basic RNN. It has four networks, each with its own set of parameters, that are activated by the sigmoid function () or the tanh function (). Each of these networks, also known as gates, has a particular role. They'll update the cell state for time step t (c^t) with the data that has to be sent on to the next time step. The element-wise transformations of the matrices that come before them are indicated by the orange circles/elipse. The gates perform the following gates do:

Forget gate layer (f): Using a function that modulates the information between 0 and 1, decides which information from the cell state to forget. Everything that is 0 is remembered, everything that is 1 is recalled, and everything in the between is a candidate.

$$\frac{dL}{df^3}=\frac{dL}{dc^3}\frac{dc^3}{df^3}=\frac{dL}{dc^3}\times c^2$$

$$\frac{dL}{dW_f}=\frac{dL}{dc^3}\frac{dc^3}{dW_f}=(\frac{dL}{dc^3}\times\tanh'(f^3)\cdot(X^3)^T)^T$$

$$\frac{dL}{dB_f}=\frac{dL}{dc^3}\frac{dc^3}{dB_f}=\frac{dL}{dc^3}\times\tanh'(f^3)$$

Input gate layer (i): This could also be a remember gate. It decides which of the new candidates are relevant for this time step also with the help of a σ function.

$$\frac{dL}{di^3}=\frac{dL}{dc^3}\frac{dc^3}{di^3}=\frac{dL}{dc^3}\times n^2$$

$$\frac{dL}{dW_i}=\frac{dL}{dc^3}\frac{dc^3}{dW_i}=(\frac{dL}{dc^3}\times\tanh'(i^3)\cdot(X^3)^T)^T$$

$$\frac{dL}{dB_i}=\frac{dL}{dc^3}\frac{dc^3}{dB_i}=\frac{dL}{dc^3}\times\tanh'(i^3)$$

New candidate gate layer (n): Creates a new set of candidates for the cell state to store. The element-wise multiplication with the input gate layer will affect the significance of these new candidates.

$$\frac{dL}{dn^3}=\frac{dL}{dc^3}\frac{dc^3}{dn^3}=\frac{dL}{dc^3}\times i^3$$
$$\frac{dL}{dW_n}=\frac{dL}{dc^3}\frac{dc^3}{dW_n}=\left(\frac{dL}{dc^3}\times\tanh'(n^3)\cdot(X^3)^T\right)^T$$
$$\frac{dL}{dB_n}=\frac{dL}{dc^3}\frac{dc^3}{dB_n}=\frac{dL}{dc^3}\times\tanh'(n^3)$$

Output gate layer (o): Which parts of the cell state are output is determined. The cell state is normalised with a tanh function and multiplied element-by-element by the output gate, which determines which new candidate from the concealed state should be output.

$$\frac{dL}{do^3}=\frac{dL}{dh^3}\frac{dh^3}{do^3}=\frac{dL}{dh^3}\times\tanh(c^3)$$
$$\frac{dL}{dW_o}=\frac{dL}{do^3}\frac{do^3}{dW_o}=\left(\frac{dL}{do^3}\times\sigma'(o^3)\cdot(X^3)^T\right)^T$$
$$\frac{dL}{dB_o}=\frac{dL}{do^3}\frac{do^3}{dB_o}=\frac{dL}{do^3}\times\sigma'(o^3)$$

IV. IMPLEMENTATION

4.1 Data Collection

The implementation of the project by using python technology, to be particularly python and R is the programming languages to implement machine learning techniques. Here we are implemented using python.

The algorithms used are Multilayer Perceptron (MLP) and Long Short Term Memory (LSTM).Data is collected from kaggle repository, data set is “Diabetic prediction using Automated ML”

4.2 Data Pre-Processing

Raw data and images from of the real world are often incomplete, inconsistent, and lacking in specific behaviors or trends. They're also likely to be plagued with errors. As a consequence, after they've been collected, they're pre-processed into a format that the machine learning algorithm can utilize to build the model. Look for null values in the dataset. Because null values are useless and empty, we don't want them in our dataset. We'll be focusing all of our efforts on "connecting" useless data rather than useful data. If we don't remove null values from our model, it will forecast results incorrectly, decreasing accuracy.

The diabetes data set originated from Kaggle Machine Learning Repository.

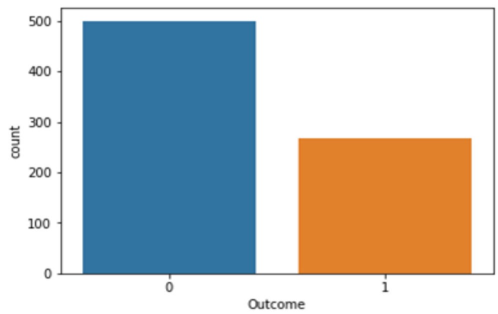
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

The diabetes data set consists of 768 data points, with 9 features each:

print("dimension of diabetes data: {}".format(diabetes.shape))

Dimension of diabetes data: (768, 9)

Outcome is the feature we are going to predict, 0 means No diabetes, 1 means diabetes. Of these 768 data points, 500 are labeled as 0 and 268 as print(diabetes.groupby('Outcome').size()).



```
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
Pregnancies                 768 non-null int64
Glucose                     768 non-null int64
BloodPressure               768 non-null int64
SkinThickness               768 non-null int64
Insulin                     768 non-null int64
BMI                         768 non-null float64
DiabetesPedigreeFunction    768 non-null float64
Age                         768 non-null int64
Outcome                     768 non-null int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

4.3 Workflow

- Collect the Dataset in Kaggle
- Preprocessing data because it has any null values or outliers its effected in output
- Split the data into 70-30 or 80-20% named as train and test
- Apply the MLP and LSTM algorithms for Train data and test
- Then we can give the input values we can predict the diabetes is rise or not

4.4 Data Visualization

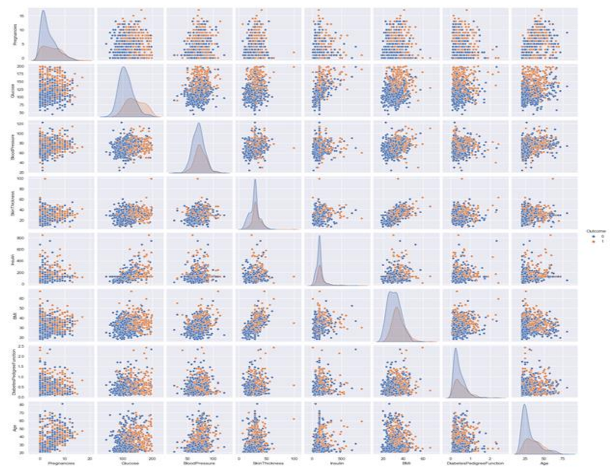
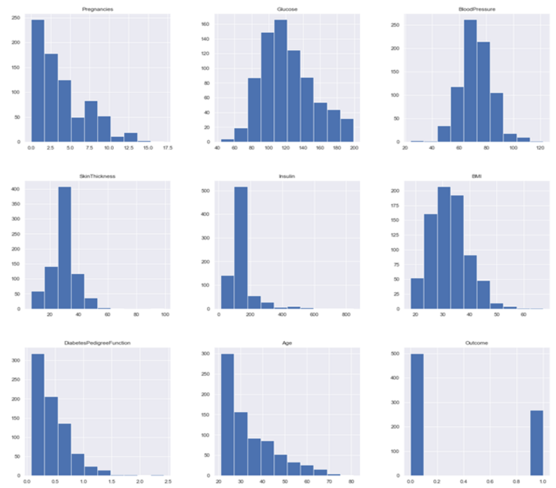


Figure 4.4.1 Pair Plot



4.4.2 Histogram

Figure 4.4.3 Heat map

V. RESULTS

Google Colab is used to implement the proposed model. The GPU provided by Colab was really helpful in training a model. We trained the model using batches to manage the memory efficiently because there are more data rows. The blood glucose prediction graph is represented in the following figures. For the user interface, we also built a web application. The online program uses the user's input factors to anticipate his or her diabetes state, and the built-in alert system assists the user in taking care of his or her health in a personalized manner, with notifications for health status and medicine remainders.

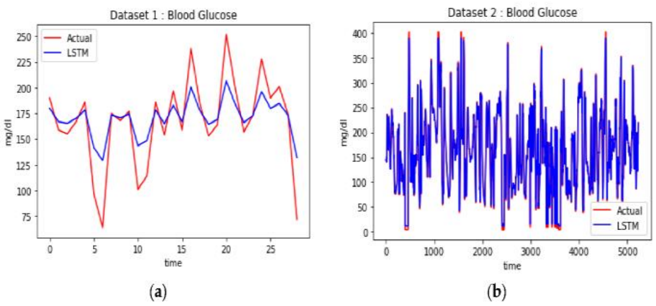


Figure 5.1 (a,b) Blood Glucose Level Prediction by LSTM

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Cite this article as :

Dr. G. R. Sakthi Dharan, Poojitha Manda, U Reshma Shravani, Annapareddy Vakula, Polumuri Sravanthi, "An App for Health Monitoring for Diabetic Patient", International Journal of Scientific Research in Science and Technology (IJSRST), Online ISSN : 2395-602X, Print ISSN : 2395-6011, Volume 9 Issue 3, pp. 168-174, May-June 2022.

Journal URL : https://ijsrst.com/IJSRST229341