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Predicting Blood Sugar Levels in Diabetic Patients Using Multi-Layer Perceptron (MLP)

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***Abstract*—Globally, Diabetes, a chronic metabolic disease having Elevated Blood sugar levels, has serious health consequences. In order to deliver individualized treatment, diabetes management requires accurate blood sugar prediction from predictive models. In this work, we examine how Multilayer Perceptron neural networks can be applied to predict blood sugar levels from blood pressure readings and insulin dosages. The Multi-Layer Perceptron (MLP) neural network design is a potent tool for making predictions about the future. MLPs are neural network architectures that consist of numerous layers of interconnected neurons, which comprise output and hidden layers. The model can recognize complex patterns and relationships because every neuron in one layer is connected to every other layer above it. A dataset comprising Blood Pressure Levels, Blood Sugar Levels, and Insulin levels, Age, BMI from individuals with diabetes has been collected. To minimize prediction errors and optimize network parameters, the backpropagation algorithm is applied.A predictive model's performance is evaluated using a Number of Measures, Sensitivity, and Mean squared Error.**

***Index Terms*—Insulin Levels, Blood Sugar Levels, Blood Pressure, Multi Layer Perception, Neural Network, ReLU Activation Function, Weight Matrices, Bias Vectors.**

I. INTRODUCTION

Diabetes mellitus, or merely diabetes, is a collection of frequently occurring endocrine conditions characterized by persistently raised blood sugar levels. Diabetes arises when the pancreas delivers insufficient insulin or when the body's cells lose tolerance to the hormone's activities. Hydration, polyuria, loss of weight, and vision impairment are some common symptoms. If not taken care of, this condition may lead to troubles with the cardiovascular system, the kidneys, vision, and neurons, besides other health issues. Untreated or improperly controlled diabetes is responsible for around 1.5 million deaths each year. The two most common kinds of diabetes are type 1 Diabetes (T1DM) and type 2 Diabetes (T2DM). Insulin replacement therapy is the most frequent treatment for type 1 diabetes, while anti-diabetic medicines and lifestyle changes can help manage type 2.

This model's superiority over others in forecasting blood sugar levels is evaluated in comparison to established methodologies such as regression models or conventional machine learning algorithms. Based on insulin levels and blood pressure data, the study showed that blood sugar levels could be reliably predicted by using an MLP neural network.

II. LITERATURE SURVEY

This study delves into the realm of predicting diabetes utilizing Multi-Layer perceptron (MLP)- Neural networks. It meticulously explores the intricacies of MLP model development tailored for diabetic patients, encompassing aspects such as data acquisition, feature curation, model architecture, and performance evaluation metrics. Through insightful discussions and empirical findings, the authors illuminate the potential of MLPs in enhancing the accuracy of diabetes predictions, thus offering significant contributions to diabetes management strategies [1]. Diabetes is a chronic disease that has become a global epidemic. Using Non-Advanced medical devices to provide diagnostic aid for diabetic condition can aid in early detection and risk assessment for many people [2]. In [3] The paper Explains about the prediction of type 2 diabetes and it's classification and the factors that are causing type 2 diabetes. In [4], [5] The authors predicted Blood Sugar Levels Using an AI model and other predicted in type 1 diabetes (T1DM) using a Neural Network. The prediction of Blood Sugar levels in prior to the actual moment helps in controlling Insulin Levels.

In [8] The Authors are Explaining the connection between Nutritional Elements that are affecting type 1 diabetes and the Blood Sugar levels in one's body. In [9] The authors evaluated Machine Learning models for detecting and predicting bad blood sugar levels (hypoglycemia) by computing pooled sensitivity and specificity estimations. In [6] Using accelerometry and CGM data from the past, the authors of this study trained models for Sugar level prediction using machine learning. This paper offers a based on data blood glucose model that predicts postprandial glycemic reactions using a decision tree gradient-boosted technique. The model considers dietary context, patient characteristics, behavioral surveys, and meal-related data from a mobile app data server [13]. In [15] They basically look at how a deep network may be built in an efficient manner if we enable expertise in the field to provide the compositional structure of the objective function along with the values of the individual functions. We investigate the problem of forecasting, based on the last few observations of a continuous glucose monitoring (CGM) device, both the blood Sugar levels and the rate at which it is changing for every 30 minutes.

III. Classification

Untreated diabetes is often linked with dehydration, and decreased body weight. A yeast infection can also cause an array of non-specific symptoms and signs, including drowsiness, blurred vision, and genitalia itching. Affected patients may also be unconscious in roughly half of cases. Type 2 grows more slowly; folks may not have symptoms for years. Type 1 arises suddenly after a preclinical stage. Diabetes-related ketoacidosis is an acute illness that usually strikes type 1 diabetes, although it can also impact type 2 if the condition has been built for an extended amount of time or if the patient has substantial cell malfunction. In critical circumstances, diminished levels of consciousness, deep breathing, also known as Kussmaul breathing, feeling nauseous, throwing up, discomfort in the abdomen, and the smell of ketones in one's breath are the hallmarks of severe body fat production.

Until 2021, 537 million persons worldwide—or around 10.5 percent of the adult population—are predicted to have diabetes. In this, maximum population upto 90 percent have type-2 Diabetes (T2DM). A 46 percent rise from current estimation is predicted for the number of individuals having diabetes by 2045, to be around 783 million, or 1 in 8.

A. Type 1 Diabetes

Based on several cases of gallstone disease and a substantial body of data, it is likely that type 2 diabetes and gallstones are related. Individuals with diabetes are more likely to develop gallstones than those without the disease. There is a connection between diabetes and cognitive impairment. Studies show that people having diabetes are more likely to develop cognitive deterioration and do so more quickly than those without the illness. Additionally, elderly patients with the condition have a higher risk of falling, particularly if they are on Insulin. Type 1 diabetes is partially hereditary; the risk of the disease is known to be influenced by several genes, including specific HLA genotypes. When someone has an inherited tendency to diabetes, several environmental factors, such as diet or viral infection, could worsen the disease.

B. Type 2 Diabetes

A condition of body cell's to be resistant to Insulin and may be combined with somewhat lower insulin levels, is a marker of type 2 diabetes. The insulin receptor is believed to be involved in the organism's decreased capacity to react to insulin. The particular challenges, however remain unknown. Cases of diabetes mellitus caused by an identified defect are classified differently. 95 percent of cases of diabetes are type 2, thus being the most prevalent kind of the disease. Changes in lifestyle or pharmaceuticals that improve the effectiveness of insulin or reduce the quantity of blood sugar created by the liver can halt or potentially repair the transition from hyperglycemia to type 2 diabetes. Type 2 diabetes is recognized to be largely influenced by a number of factors, including stress, eating Non healthy foods, lack of physical activity, obesity (defined as a BMI of greater than 26), and urbanization.

IV. Methodology

Insulin level plays an important role to calculate blood sugar level. When our body consumes carbohydrates, it breakdowns into glucose and enters our blood flow. In response, pancreas releases insulin in our bloodstream, which allows the cells in our body to consume insulin, then glucose is either used as an Energy source or stored. Another factor which is helpful in predicting blood sugar level is Blood pressure. Blood pressure Levels provide Information about how the cardiovascular system impacts Blood Sugar Levels in the body. Whenever a person is having high blood pressure, he/she has a chance of having insulin resistance in their body. Elevated amount of blood pressure also leads to increment of sympathetic nervous system activity which often leads to stress and in return influences glucose metabolism and promotes releasing of stress hormones. These hormones raise the blood sugar level through various mechanisms.

Multilayer perceptron (MLP) is basically an artificial neural network, which is having fully connected neurons with a nonlinear type of activation function, having more than three layers and marking it's presence for being able to seperate data that is impossible to seperate linearly. Since these are fully connected, each neuron in each layer connects with a corresponding weight of every neuron in the next upcoming layer. This adds multiple hidden layers between the output and input layers and results in transforming the output of a hidden layer. There are several types of activation functions which includes ReLU function, Tanh function, Sigmoid function etc... Here, we have used ReLU activation Function for transforming the outputs of the hidden layer.

A. Model Simulation and Initialisation

In this Model, The Input layer has two Neurons for two parameters which are Insulin and Blood Pressure. There are three hidden layers, each using their respective ReLU activation function. The outer layer will be having a single neuron since we're predicting a single value. This Model of predicting Blood Sugar Levels is compiled using Mean Squared Error (MSE) as the loss Function with a learning rate of 0.0001. Techniques such as batch size management, sufficient number of training epochs, validation split, and the use of the Adam optimizer all together contribute to minimize prediction errors, leading to a robust and accurate predictive model. As Input features, the training data consists of insulin levels and Blood Pressure levels as "insulin train normalised" and "blood pressure train normalised" and blood Sugar levels as the target value. This MLP Neural Network Model is trained for 2000 data Entries with a batch size of 16.

- Let I be Insulin Level
- Let BP be Blood Pressure
- Let BS be Blood Sugar Level

The Equation for predicting the values of Blood Sugar Levels is as follows.

$$\mathrm{BS} = \mathrm{f}_{\mathrm{output}}\ (\mathrm{f}_{32}\,(\mathrm{f}_{64}\,(\mathrm{f}_{128}\,([\mathrm{I}, \mathrm{BP}].\mathrm{W}_{\mathrm{hidden}\ 1} + b_{\mathrm{hidden1}}\ ).\ \mathrm{W}_{\mathrm{hidden}\ 2} + \mathrm{b}_{\mathrm{hidden2}}\ ).\ \mathrm{W}_{\mathrm{hidden}} + \mathrm{b}_{\mathrm{hidden3}}\ ).\mathrm{W}_{\mathrm{output}}\ + \mathrm{b}_{\mathrm{output}}\ )$$

- f_{128}, f_{64}, f_{32} are the ReLU Activation functions applied to outputs of respective hidden layers.
- $[I, BP]$ are the input features.
- W_{hidden1}, W_{hidden2}, W_{hidden3} are the weight matrices of hidden layers.
- b_{hidden1}, b_{hidden2}, b_{hidden3} are the bias vectors of hidden layers.
- W_{output} is the Weight Matrix and b_{output} is the bias vector of the outer layer.
- f_{output} is a Linear Activation Function.

Weight Matrices represents the strength of the connection between the parameters and gives their according to that. Bias vectors are additional parameters applied to each neuron in a layer. When a neural network processes input data, each neuron calculates a weighted sum of the input values, plus a bias factor.

The bias term enables the neuron to change its output independent of the input. Prior to applying the activation function, the weighted total is increased by the bias factor represented by (b). In the Model, Each feature (Insulin Levels, Blood Pressure Levels, Age, BMI) are given as input and processed through multiple layers of neurons. Each hidden layer computes a sum of weights of the inputs from the preceeding layer and applies activation function to it. Backpropagation is used to update the weights and bias to minimize the error during training.

B. Model Training

The Rectified Linear Activation function or ReLU is a piecewise function that has become the default activation function for this Neural Network because the model which uses this activation function is easy to train and mostly gives the best results. In predicting the Blood Sugar Levels, the Artificial Neural Network model used this activation function. The dataset is loaded and the required parameters such as Insulin Levels, Blood Pressure and Blood Sugar Levels are extracted from the dataset. The model Understands the Relation Between Blood Sugar Levels and both the parameters mentioned from the dataset and gives the predicted values. The Blood Sugar Levels are plotted against Blood Pressure Levels and Insulin Dosages using a Scatter Plot as seen in the Fig.1

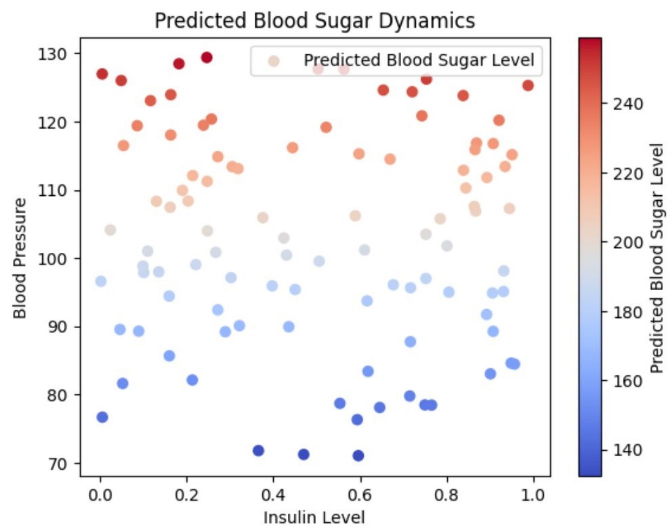

Fig. 1. Predicting Blood Sugar Levels

We have also predicted whether the patient is having type 1 or type 2 diabetes by taking the factors like Age, BMI into consideration. Age increases the risk of getting Diabetes. Younger one's mostly get type 1 and while older get type 2. These values are Extracted from the dataset available. A function is defined to predict the type of diabetes. It predicts type 1 diabetes if the patient's age is less than 50 and BMI is greater than 30, Otherwise it gives the output as type 2. These predictions are plotted in a graph as shown in Fig.2.

The dataset which we are using here in this model is taken from the National Institute of Diabetes and Digestive and Kidney Diseases. The primary goal of the dataset is to forecast a person's likelihood of developing diabetes or not using specific diagnostic metrics and dataset-included characteristics. However,we are using same dataset for predicting Blood Sugar Levels by taking only our useful parameters from the dataset. Several limitations were applied to the selection of the data of the parameters Insulin and Blood Pressure from a bigger database. All of the patients here are Pima Indian ladies over the age of 21. The MSE loss function has been applied to calculate the variation between the Actual Blood Sugar Levels with those of the sugar levels predicted by the model.

C. Architecture of MLP and Optimization

- INPUT LAYER: The kind of dataset you are considering here will determine the size of the input layer. Here, in this case we might take Carbohydrate intake, Time of the

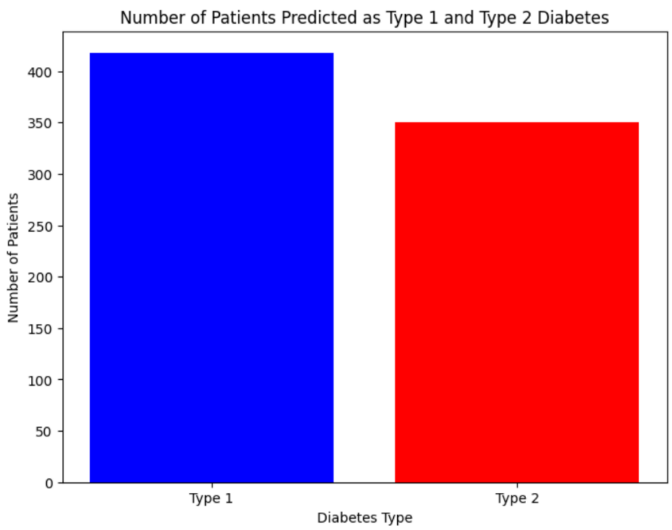

Fig. 2. No. of Patients having type1 and type2 Diabetes in our Dataset

day, Blood Pressure Levels, Insulin Levels. But mainly we considered Blood Pressure and Insulin.

- HIDDEN LAYER: Usually, An MLP model which is based on a time series prediction might have 2-4 hidden layers.
- OUTPUT LAYER: For regression type of prediction like this the output layer will have only single neuron.

V. Conclusion

The real Blood Sugar Levels which are in the dataset and the predicted Blood Sugar Levels are plotted against a sample index. In order to clearly see the Difference between them, the dataset is decreased to 100 data values. This visualization shows how well the model's prediction is as compared to Actual Blood Sugar Levels. A line Chart is plot against the sample Index as shown in Fig.3.

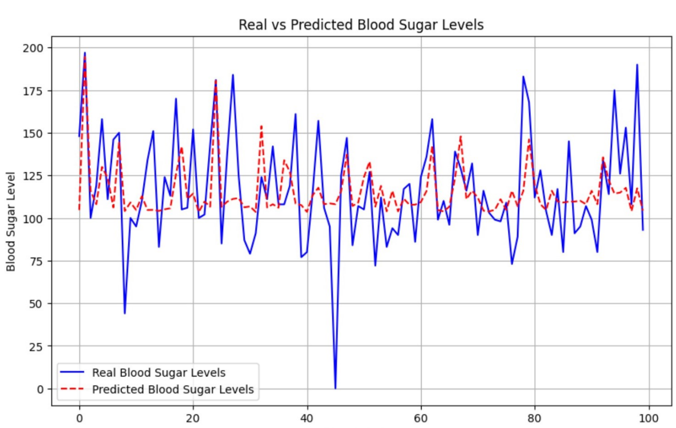

Fig. 3. Real Vs Predicted Blood Sugar Levels

VI. Results and Future Scope

In this study, we looked at the possibility of utilizing MLP models to predict blood sugar levels. By research and analysis, we established the accuracy of our approach in properly predicting blood sugar levels, as seen by the scatter plot and also displaying the association between predicted and real blood sugar levels. Also, we studied the effectiveness of age and BMI in differentiating between type 1 and type 2 diabetes, getting valuable insights into the parameters that influence diabetes classification.

Our findings highlight the importance of using machine learning techniques, specifically MLP models, for blood sugar level prediction and diabetes classification. We can improve early detection by using widely available data such as insulin, blood pressure, age, and BMI. Future study could concentrate on improving MLP models using advanced optimization approaches, investigating signals other than insulin and blood pressure to increase prediction accuracy, and using different data sources for thorough modelling. Clinical validation and ongoing research are crucial for determining real-world applicability and understanding the changing patterns of diabetes progression. Making therapies based on individual patient profiles can be developed through machine learning and personalized medical approaches, moving diabetes management and healthcare delivery closer to individualized, data-driven solutions.

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