Email: editor@ijerst.com or editor.ijerst@gmail.com

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

INTELLIGENT SYSTEM FOR PREDICTING DIABETES AND PERSONALIZED INSULIN DOSAGE

[1]Manugonda Manohar, MCA Student, Department of MCA
[2] Emmanuel Raju A, M.tech, Assistant Professor, Department of MCA
[12]Dr KV Subba Reddy Institute of Technology, Dupadu, Kurnool

ABSTRACT

Elevated glucose (blood sugar) levels are a hallmark of diabetes, a metabolic disease that may last for years. Insulin, a hormone secreted by the pancreas, generally controls blood sugar levels in the body. However, high blood sugar levels result from either inadequate insulin synthesis or cells' inability to react to insulin in people with diabetes.

In order to keep blood sugar levels within a specified range, people with diabetes must take medicine, follow a certain diet, exercise regularly, and check their blood sugar levels. Complications such as cardiovascular disease, renal damage, nerve damage, and vision difficulties may arise from uncontrolled diabetes.

Linear Regression technique for insulin dose prediction in diabetic patients and Gradient Boosting Classifier for diabetes prediction. You want to train the models using the PIMA diabetes dataset and then utilise the UCI insulin dosage dataset to forecast insulin dose.

You have decided to train the Gradient Boosting Classifier on the PIMA diabetes dataset and use the UCI insulin dosage dataset to predict insulin dose. Obtain these datasets and ensure they are in the correct format for your machine learning techniques. It is possible that pre-processing the datasets is necessary prior to training the models. Data normalisation, feature separation, and addressing missing values are all possible steps in this process.

When training a Gradient Boosting Classifier, make use of the PIMA diabetes dataset. The existence of diabetes may be predicted by this algorithm by learning patterns and correlations in the data. After training the classifier, you'll want to submit a test dataset that doesn't have any class labels. Make a diabetes diagnosis prediction for every test dataset sample using the learnt model.

Using the UCI insulin dosage dataset, you can forecast the insulin dose for samples that the Gradient Boosting Classifier has predicted to have diabetes. Extract important characteristics for insulin dose prediction and preprocess the information as needed. The UCI insulin dose dataset that has been pre-processed in order to train a Linear Regression model. The model will figure out how to take insulin doses based on the characteristics fed into it.

Apply the trained Linear Regression model on the samples that the Gradient Boosting Classifier predicted to have diabetes. Each sample's insulin dose will be predicted by the model.

Compare and contrast how well the Linear Regression and Gradient Boosting

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

Classifiers performed. One way to measure how well the models work is by looking at their accuracy, precision, recall, and mean squared error (MSE).

I. INTRODUCTION

1.1 Introduction

Hyperglycemia owing to insufficient insulin production, ineffective insulin action, or both characterises diabetes mellitus, a class of metabolic disorders. The prevalence of diabetes has been increasing at a faster rate in middle- and low-income countries. The number of persons diagnosed with diabetes has risen from 108 million in 1980 to 422 million in 2014.

A failure to produce enough insulin or an inadequate response to insulin are the two main causes of diabetes symptoms. Diabetics need to take their insulin as directed in order to maintain controlled glucose levels. The patient's expert must also decide the appropriate insulin dose based on the patient's historical dosage data and their continuously monitored glucose levels.

The three main types of diabetes are: According to conventional wisdom, the immune system mistakenly assaults healthy cells, resulting in type 1 diabetes and its subtypes (type 2, type 1a, and gestational diabetes). This response shuts down the insulin synthesis. Of all people with diabetes, 5–10% will develop type 1 diabetes. Symptoms of type 1 diabetes may sometimes worsen quickly. Typically, it affects younger generations, such as children, teenagers, and young adults. If you're living with type 1 diabetes, you have to take insulin shots daily. No one knows of a way to stop type 1 diabetes from happening just yet.

Second-Type Diabetes: Type 2 diabetes is characterised by impaired insulin action and the inability to maintain normal blood sugar levels. Of all people with diabetes, 95% to 95% have type 2. Although adults are the typical victims, it gradually spreads to younger generations, affecting children, teenagers, and young adults as well. You must have your blood sugar checked if you are at risk, whether of whether you are experiencing any symptoms or not. A healthier lifestyle, including: • Regular exercise. • A diet rich in whole foods, may reduce the risk of developing type 2 diabetes or at least put it off for a later date.

• Taking part.

Diabetes I Women who have never had diabetes before get pregnant and acquire gestational diabetes. The risk of complications for your unborn child increases if you have gestational diabetes. In most cases, gestational diabetes goes away after the baby is delivered. But it increases your risk of developing type 2 diabetes in old age. Your unborn kid is more likely to grow up to be overweight and have type 2 diabetes.

More than one-third of the adult population in the United States has prediabetes, which affects 96 million people. Most people with it (over 80%) don't even know they have it. When glucose levels in the blood are elevated but still below the cutoff for a type 2 diabetes diagnosis, a person is said to have prediabetes. This should serve as a red flag. Stroke, heart disease, and type 2 diabetes are more common in those with prediabetes.

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

The good news is that... You may take positive actions to reverse prediabetes with the help of a CDC-approved lifestyle modification program.

In life-threatening situations, like as hypoglycemia, glucose focus predictions might coordinate with the appropriate patient reaction. Due to this, several recent research have considered using sophisticated data-driven methodologies to build accurate glucose metabolism prediction models.

In addition to the patient's usual self-care practices, certain diabetes board frameworks have been suggested to aid patients even more with managing their condition on their own. The predictive display of glucose digestion is an essential component of a diabetic board structure.

Methodology

Patients with diabetes will be able to anticipate their insulin dosages thanks to this project's use of a Gradient Boosting Classifier for diabetes prediction and a Linear Regression algorithm for insulin dosing prediction. The PIMA diabetes dataset and the UCI insulin dosage dataset will be used in the execution of this research.Predicting the presence or absence of diabetes in patients using the diagnostic metrics provided in the PIMA dataset is the main purpose of the dataset.In order to conduct empirical analyses of machine learning algorithms, the machine learning community makes use of the UCI Machine Learning Repository, which is a compilation of databases, domain theories, and data generators. We are using the aforementioned dataset to train both algorithms. After training is complete, we will upload a test dataset without class labels. Linear Regression will be used to predict insulin dose if diabetes is found by Gradient Boosting, while Gradient Boosting will be used to predict the existence of diabetes.

1.2 Problem statement

Elevated blood glucose levels caused by insufficiencies in insulin production, action, or both characterise a group of metabolic disorders known collectively as diabetes mellitus. There are mainly two forms of diabetes: type 1 and type 2. pancreas, leading to an insulin deficiency. diverse secretions mixed. In addition to the standard practices that patients already follow, many diabetes management systems have been introduced to provide patients with even more support in self-management.

1.3 Objectives

Diabetes management solutions rely on glucose metabolism prediction modelling. In life-threatening emergencies like hypoglycemia, it is crucial for patients to be able to predict their glucose levels. This is why many new research have looked at state-of-the-art data-driven approaches to develop accurate glucose metabolism prediction models.

II. LITERATURE SURVEY

Extreme learning machines for water demand forecasting

CO-WRITERS: Kazimierz Adamowski, Jan Adamowski, and Mukesh Tiwari

In this abstract, Various modelling techniques for daily urban water demand predictions with limited data are discussed in the offered material. Here, we will look into ELM modelling techniques, either on

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

their own or in conjunction with wavelet analysis (W) and bootstrap (B) techniques. Traditional models based on artificial neural networks (ANN, ANNW, ANNB) are contrasted with ELM-based models (ELM, ELMW, ELMB) in terms of their performance.

In order to create the urban water demand forecasting models, the research used climate and water demand records for the Canadian city of Calgary spanning three years.

In addition, when comparing the ELMW model to the ANNW and ANNB models, the former showed a considerable improvement in forecasting peak urban water demand. Accordingly, it seems that the urban water demand model's overall performance is much improved by using wavelet processing.

It seems that the above content is an extract or synopsis of a longer research paper or study. This data sheds light on how various modelling approaches for predicting urban water demand stack up against one another.

Devi; M. Renuka; and J. Maria Shyla are the authors.

In order to better detect patients' illnesses, data mining techniques are being used. A number of bodily systems might feel the effects of diabetes mellitus, a chronic condition. Human lives can be saved and illnesses can be controlled by early prediction. Using a variety of data mining approaches, this research investigates the possibility of diabetes early prediction. In order to assess the precision of the data mining methods for making predictions, the dataset has used 768 examples from the PIMA Indian Dataset. The results show that compared to other methods, Modified J48 Classifier provides the best accuracy.

Diabetes Mellitus Prediction via Data Mining

Mr. K. Aravind Kumar, J. Steffi, and Dr. R. Balasubramanian are the authors.

In this abstract, An increase in blood sugar levels leads to diabetes, a chronic condition. A number of automated information systems that use different classifiers to detect and predict diabetes were described. The use of data mining techniques aids in the diagnosis of patients' illnesses. A number of bodily systems might feel the effects of diabetes mellitus, a chronic condition. Human lives can be saved and illnesses can be controlled by early prediction. It is obvious that the accuracy and competence of the system are enhanced by using genuine classifiers. Diabetes mellitus unfairly affects more and more households as its prevalence continues to rise. Prior to their diagnosis, the majority of diabetics are unaware of the risk factors they face. Using data mining methods, this research investigates the possibility of diabetes early prediction. To find out how well the data mining methods for making predictions work, the dataset has used 768 cases from the PIMA Indian Diabetes Dataset. Using the data in the dataset, we created five prediction models with nine input variables and a single output variable; we then tested each model using the F1 Score and other metrics for accuracy, precision, sensitivity, and specificity. In order to predict diabetes based on common risk factors, this research aims to analyse the performance analysis of several models,

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

including Naïve Bayes, Logistic Regression, Artificial Neural Networks (ANNs), C5.0 Decision Tree, and Support Vector Machine (SVM). Index Terms—Data mining, Prediction, Naïve Bayes, Logistic Regression, C5.0 Decision Tree, Artificial Neural Networks (ANN), and Support Vector Machine (SVM)—Gave the best classification accuracy, followed by the logistic regression model, ANN, and finally, the decision tree model (C5.0).

Diabetes Mellitus Prediction Using Data Mining Methods: A Comparison

Written by: Sunge Aswan Supriyadi

In this abstract, A condition characterised by persistently high blood sugar levels is known as diabetes. In order to detect and prevent diabetes, a number of automated algorithms have been developed. The patient's illness can be better diagnosed using one data mining strategy. With the use of forecasts, we can start preventing diseases before they strike patients, which may save lives. As you go through the tiers, picking a valid categorisation obviously increases the system's truth and accuracy. Prior to their diabetes diagnosis, the majority of people with the disease had no idea what dangers they faced. Based on the data in the dataset, five prediction models are constructed utilising nine input variables and a single output variable. The researchers set out to evaluate the accuracy of many models for diabetes mellitus prediction using Naive Bayes, Decision Tree, Support Vector Machine, K-NN, and Artificial Neural Networks (ANNs).

III. SYSTEM ANALYSIS & SYSTEM DESIGN

Existing System

Using data mining techniques like k-means, a diabetes prediction system is developed. Data mining is useful for helping doctors diagnose patients' illnesses. The PIMA Indian Dataset, including 768 instances, was used in this study. In order to make early diabetes predictions, they used a number of data mining techniques. Finding out how well these methods worked in terms of making accurate predictions was the main objective. The Modified J48 Classifier has the makings of a valuable tool for early diabetes prediction due to its high accuracy. Be advised that this research only looked at the PIMA Indian Dataset, hence its results may not be generalisable to other populations or datasets. To verify that the Modified J48 Classifier is effective for diabetes prediction, more study and validation using other datasets and demographics would be advantageous. When it comes to managing diabetes mellitus, insulin dose prediction is very vital. Using the K-Means clustering technique, this work develops an expert system to forecast the ideal insulin doses. To provide tailored suggestions, the algorithm takes into account patient details, blood glucose levels, and past insulin doses.

Disadvantages System

- The effectiveness of this model is significantly impacted by data that is either missing or unavailable due to technological difficulties.
- Scan and sorting the datasets takes considerably more time, which is another drawback.
- Nonetheless, owing to the complicated reliance on several

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

variables, early diabetes prediction poses a significant challenge for medical practitioners.

Proposed System

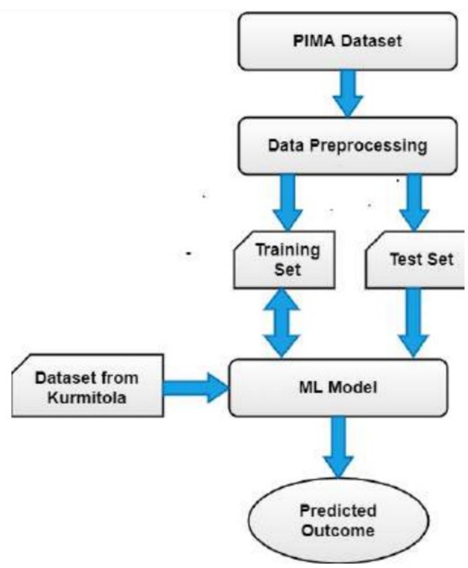
- Two separate algorithms are being trained using the PIMA diabetes dataset and the UCI insulin dosage dataset. The first method, Gradient Boosting, is being trained to predict if diabetes is present. If diabetes is found by Gradient Boosting, the second strategy, Linear Regression, is being trained to predict insulin dose.
- The PIMA diabetes dataset and the UCI insulin dose dataset have been selected for your research.
- • The first step is training a Gradient Boosting algorithm to detect diabetes using the PIMA dataset.
- b. In addition, if diabetes is found, you may forecast insulin dose by training a Linear Regression model on the UCI insulin dosage dataset.
- In the testing phase, you may see how well your trained models performed by uploading a dataset that does not include any class labels (such as whether or not a patient has diabetes).
- b. You forecast if each occurrence in the test dataset has diabetes using the learnt Gradient Boosting model.
- c. In the event that Gradient Boosting identifies diabetes, the insulin dose may be predicted using the learnt Linear Regression model.
- You want to forecast if diabetes is present and, if so, the dose of insulin to use by merging these two algorithms. The initial prediction of diabetes is provided using Gradient Boosting, and the insulin dose is estimated using Linear Regression.

Advantages System

- Predicting an individual's insulin dosage or blood glucose level with any degree of accuracy is probably not feasible due to how unpredictable these variables are.
- Predicting the patient's average blood glucose level over 24 hours and if their glucose level would be high are both made easier.
- It's useful for ensuring that diabetic patients get the correct dose of insulin.
- The body can operate normally and the life of the individual can be saved when insulin is administered at the appropriate moment.

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE:



V. SYSTEM IMPLEMENTATION

MODULES

Many modules, each with its unique set of features, have been used in this project.

We uploaded the user datasets for Pima Indian diabetes and UCI Insulin dose in the Diabetes Insulin Disease upload.

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

To put the Gradient Boosting Algorithm into action, we first import the dataset and then train it.

Run the algorithm for linear regression: The dataset is trained using the Gradient Boosting Algorithm first, and then the insulin dose quantity is predicted using the Linear Regression Algorithm.

The datasets are trained, and then the Gradient Boosting Algorithm and Linear Regression Algorithm are used to estimate the quantity of insulin dose and diabetes.

Data Visualisation: The performance graph, displaying the relative accuracy of the two methods, is now shown in this module.

VI. SCREEN SHOTS

Dataset :

Seven hundred sixty-eight women residing in or around Phoenix, Arizona, USA, are included in the PIMA Indian Diabetes Dataset, which was first compiled by the National Institute of Diabetes and Digestive and Kidney Diseases. Two hundred fifty-eight people tested positive for diabetes, whereas 500 people tested negative. As a result, there is a single dependent variable and eight independent variables (TYNECKI, 2018): age, blood pressure, skin thickness, insulin, body mass index (BMI), pedigree diabetes function, and the number of pregnancies. Since 1965, the Pima population has been studied every two years by the National Institute of Diabetes and Digestive and Kidney Diseases. Due to the fact that type 2 diabetes is thought to be caused by a combination of hereditary and environmental variables, the Pima Indians Diabetes Dataset contains information about characteristics that may or may not be associated with the development of diabetes and its implications.

Machine learning models for diabetes diagnosis and insulin dose prediction.

Patients with diabetes will be able to anticipate their insulin dosages thanks to this project's use of a Gradient Boosting Classifier for diabetes prediction and a Linear Regression algorithm for insulin dosing prediction. The PIMA diabetes dataset and the UCI insulin dosage dataset will be used in the execution of this research.

After we train both algorithms on the aforementioned dataset, we will upload a test dataset without class labels. If Gradient Boosting detects diabetes, Linear Regression will determine the insulin dose.

You can find both datasets in the Dataset folder, and the details of each are shown on the screen below.

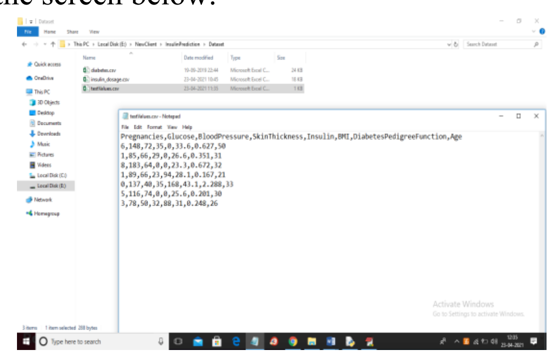


Fig.1. dataset

Both datasets are visible in the folder shown above. The testValues.csv file does not have a class label for diabetes, which may be either 0 (no diabetes found) or 1 (diabetes identified). Using the aforementioned test results, the Gradient Boosting algorithm can forecast the insulin dose, while linear regression can forecast the class label.

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621

Vol. 21, Issue 2, 2025

Run Code

To run project double click on 'run.bat' file to get below screen.

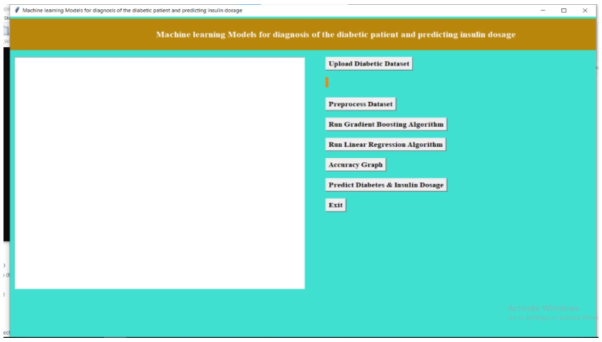


Fig. 2.Run Code

Upload Diabetic Dataset

The dataset, which includes variables like gestational age, blood sugar levels, and blood pressure, was compiled from the PIMA Diabetes Dataset and the UCI Insulin Dosage Dataset; to access it, go to the dataset folder and select the "Upload Diabetic Dataset" button. after choosing and uploading the whole 'Dataset' folder to bring up the insulin and diabetes datasets, and then clicking the 'Select Folder' button, we get the insulin dosage dataset and the diabetes dataset.

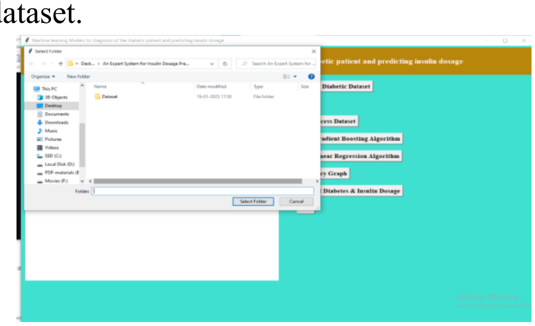


Fig.3 diabetic dataset

Dataset Loaded

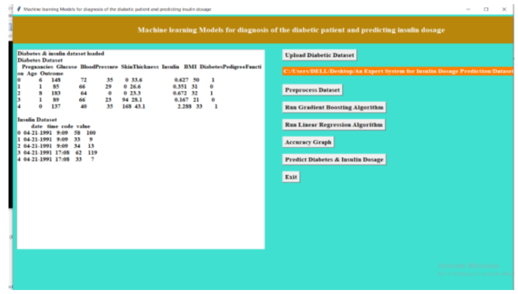


Fig. 4 dataset loaded

Both datasets are loaded in the above screen, and we can view several records from each. Additionally, we will obtain a graph below.

Fig.5. graph

The presence of diabetes is shown in each column of the above graph by red dots, while the absence of diabetes is represented by blue dots.

To display the presence or absence of diabetes for each column value, we are creating graphs. For instance, in the first column of the given graph, we are plotting the 'number of pregnancies' with the 'presence or no presence of diabetes' value. After that, we can close the graph and proceed to remove missing values and split the dataset into train and test sets by clicking the 'Preprocess Dataset' button.

Pre process Dataset

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

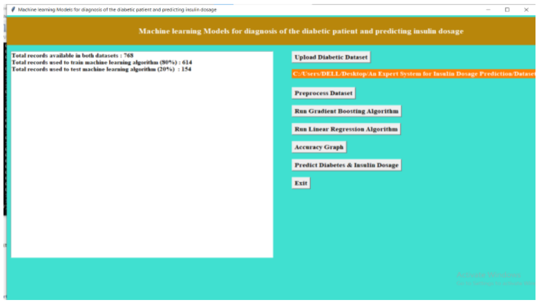


Fig.6. Pre-process Dataset

Preprocessing the dataset is the next stage. You can see the number of records used to train and test the dataset using the Machine Learning Algorithm, as well as the total number of records in both datasets, on the page that appears when you click the Preprocess Dataset button.

The dataset is now ready for use because we have trained and tested it, as seen in the above screen. It has 768 records in total, with 80% of those records going towards training and 20% towards testing the ML accuracy. Running the dataset through the Gradient Boosting Algorithm to forecast patients' diabetes is the next logical step, and we can now utilise the dataset for this purpose.

Gradient Boosting Algorithm

To train gradient boosting using the aforementioned dataset to forecast patients' diabetes, click the "Run Gradient Boosting Algoritham" button.

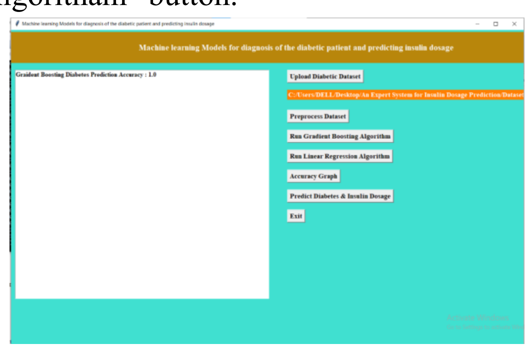


Fig .7. Gradient Boosting Algorithm

We can see that the gradient enhancing accuracy is 100% on the displayed screen. With a prediction accuracy of 100%, the Gradient Boosting Algorithm can determine whether a patient has diabetes. After the Gradient Boosting Algorithm identifies diabetic individuals, we apply the Linear Regression Algorithm to forecast the insulin dose quantity for these patients.

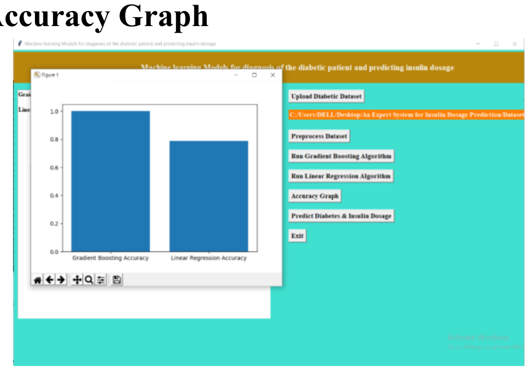
Linear Regression Algorithm

Fig.8. Linear Regression Algorithm

After the Gradient Boosting Algorithm we use the Linear Regression Algorithm to predict the insulin dosage amount for the diabetic patients which is detected by the Gradient Boosting Algorithm.

In above screen with linear regression Algorithm we got 78% accuracy compared to Gradient Boosting Algorithm the linear regression algorithm accuracy is less but it gives maximum accuracy to predict the insulin dosage amount for the diabetic patients

Accuracy Graph



Int. J. Eng. Res. & Sci. & Tech. 2025

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621

Vol. 21, Issue 2, 2025

Fig .9. Accuracy graph

After we run the Linear Regression Algorithm next step is the Accuracy graph that is how much accuracy both the algorithms are giving that is shown in the form of graph. By clicking on the 'Accuracy Graph' button we can get the Accuracy graph.

Next step is to predict the diabetes and insulin dosage amount for the patients who are having diabetes.

Predict diabetes and insulin dosage

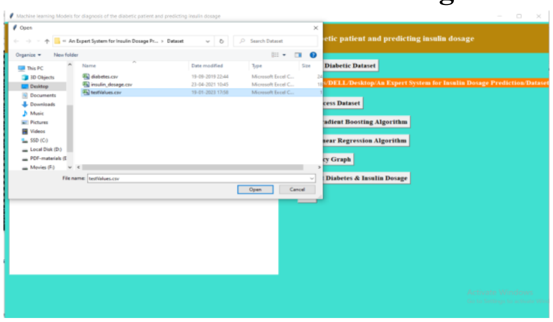
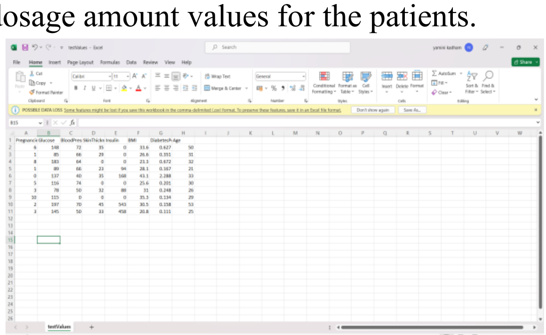


Fig.10. predict diabetes and insulin

To predict the diabetes and insulin dosage amount we have to select and upload 'testValues.csv' file and then click on 'Open' button to get the values of diabetes and insulin dosage amount. All the trained and tested data is stored in the 'testValues.csv' file.

By selecting the file and uploading it we get the final result which is diabetes and insulin dosage amount values for the patients.



In the above screen when we observe the 11th record the values are taken randomly and save it. After that upload the test values set and it will predict whether a patient is diabetic or not ,if a patient is diabetic it will predict the insulin dosage.

It predicts the patient is diabetic and also predicts the required insulin dosage for the patient.

Result

Using the Gradient Boosting Algorithm, we can see the test values taken by various parameters in the square brackets above the screen. If diabetes is detected, linear regression will predict the amount of insulin dosage that diabetic patients need to take for their health. The predicted result is either "No Diabetes Detected" or "Diabetes Detected" after the square brackets.

If diabetes is found, it tells the patient how much insulin to take; if it is not, it says "No Diabetes Detected," which is OK with the patients.

VII. CONCLUSION

This article details research that employed a neural network model to

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

determine how much insulin to give diabetic patients. The research model in question was a Gradient Boosting with Backpropagation (BP)–based one. Every patient's gender, height, weight, and blood sugar level are the four input factors that the model uses. Researchers used information from 180 patients to do tests. If diabetes was diagnosed, the insulin dose was predicted using the Linear Regression Algorithm. The Gradient Boosting Algorithm was used for diabetes prediction. Results showed that the Gradient Boosting Algorithm outperformed the Linear Regression Algorithm and converged quickly, as stated in the article. Accordingly, the Gradient Boosting model seems to have done a better job at diabetes prediction and insulin dosing for those with diabetes.

REFERENCES

[1] Cho, J., Choi, Y. J., Sohn, J., Suh, M., Cho, S. K., Ha, K. H., ... & Shin, D. C. (2015). Ambient ozone concentration and emergency department visits for panic attacks. Journal of Psychiatric Research, 62, 130-135.

[2] Power, M. C., Kioumourtzoglou, M. A., Hart, J. E., Okereke, O. I., Laden, F., & Weisskopf, M. G. (2015). The relation between past exposure to fine particulate air pollution and prevalent anxiety: observational cohort study. bmj, 350.

[3] Rotko, T., Oglesby, L., Künzli, N., Carrer, P., Nieuwenhuijsen, M. J., & Jantunen, M. (2002). Determinants of perceived air pollution annoyance and association between annoyance scores and air pollution (PM2. 5, NO2) concentrations in the European EXPOLIS study. Atmospheric Environment, 36(29), 4593-4602.

[4] Llop, S., Ballester, F., Estarlich, M., Esplugues, A., Fernández-Patier, R., Ramón, R., ... & Iñiguez, C. (2008). Ambient air pollution and annoyance responses from pregnant women. Atmospheric Environment, 42(13), 2982-2992.

[5] Brook, R. D., Rajagopalan, S., Pope III, C. A., Brook, J. R., Bhatnagar, A., Diez-Roux, A. V., ... & Kaufman, J. D. (2010). Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. Circulation, 121(21), 2331-2378.

[6] Cho, J., Choi, Y. J., Sohn, J., Suh, M., Cho, S. K., Ha, K. H., ... & Shin, D. C. (2015). Ambient ozone concentration and emergency department visits for panic attacks. Journal of Psychiatric Research, 62, 130-135.

[7] Sass, V., Kravitz-Wirtz, N., Karceski, S. M., Hajat, A., Crowder, K., & Takeuchi, D. (2017). The effects of air pollution on individual psychological distress. Health & place, 48, 72-79.

[8] Rotko, T., Oglesby, L., Künzli, N., Carrer, P., Nieuwenhuijsen, M. J., & Jantunen, M. (2002). Determinants of perceived air pollution annoyance and association between annoyance scores and air pollution (PM2. 5, NO2) concentrations in the European EXPOLIS study. Atmospheric Environment, 36(29), 4593-4602.

[9] Xu, W., Ding, X., Zhuang, Y., Yuan, G., An, Y., Shi, Z., & Hwa Goh, P. (2020). Perceived haze, stress, and negative

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp610-621
Vol. 21, Issue 2, 2025

emotions: An ecological momentary assessment study of the affective responses to haze. Journal of health psychology, 25(4), 450-458.
[10] Lu, J. G., Lee, J. J., Gino, F., & Galinsky, A. D. (2018). Polluted morality: Air pollution predicts criminal activity and unethical behavior. Psychological science, 29(3), 340-355