EAI Endorsed Transactions
on Scalable Information Systems

Research Article EAI.EU

A Novel Approach for Prediction of Gestational Diabetes based on Clinical Signs and Risk Factors

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Abstract

Gestational diabetes mellitus occurs due to high glucose levels in the blood. Pregnant women are affected by this type of diabetes. A blood test is to be performed to identify diabetes. The Oral Glucose Tolerance Test (OGTT) is a blood test performed between the 24th and 28th week of pregnancy that is necessary to identify and overcome the side effects of GDM. The main objective of this work is to train a model by utilizing the training data, evaluate the trained model using the test data, and compare existing machine learning algorithms with a Gradient boosting machine (GBM) to achieve a better model for the effective prediction of gestational diabetes. In this work, the analysis was done with a few existing algorithms and the Extreme learning machine and Gradient boosting techniques. The k-fold cross-validation technique is applied with values of k as 3, 5, and 10 to obtain better performance. The existing algorithms implemented are the Naive Bayes classifier, Support Vector Machine, K-Nearest Neighbour, ID3, CART and J48. The proposed algorithms are Gradient boosting and ELM. These algorithms are implemented in R programming. The metrics like accuracy, kappa statistic, sensitivity/Recall, specificity, precision, f-measure and AUC are used to compare all the algorithms. GBM has obtained better performance than existing algorithms. Then finally, GBM is compared with the other proposed robust Machine Learning algorithm, namely the Extreme learning machine, and the GBM performed better. So, It is recommended to use a gradient-boosting algorithm to predict gestational diabetes effectively.

Keywords: Gestational diabetes mellitus (GDM), Naive Bayes (NB) classifier, Support Vector Machine, K-Nearest Neighbour (KNN), ID3, CART, J48,k-fold cross-validation, Extreme learning machine (ELM).

Received on 14 September 2022, accepted on 12 December 2022, published on 11 January 2023

doi: 10.4108/eetsis.v10i3.2697

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1. Introduction

GDM occurs in pregnant women with high blood glucose levels due to insufficient insulin production by the pancreas. Every GDM patient must take proper treatment to avoid complications. Specific measures like physical exercises are to be taken to control gestational diabetes. The chance of affecting GDM is high if a pregnant woman has a previous history of GDM or obesity, or pre-diabetes [1]. A pregnant woman can identify the symptoms of gestational diabetes, like polyuria, polydipsia, polyphagia, and blurred vision. Every pregnant woman must take a proper test to detect diabetes in the early stage [2]. Long time suffering from GDM results in many complications like miscarriage, preterm delivery, excessive birth weight, nephropathy, high blood pressure, future type-2 diabetes and cardiovascular disease. GDM affects the growth of the foetus during pregnancy [3].

If GDM remains untreated for a long time, it may lead to cesarean delivery and affect the birth baby's organs. The baby may suffer from breathing disorders [4]. GDM can be prevented if the patient follows a simple routine like maintaining a healthy diet, ideal body weight, and regular physical exercise.

Table 4.4 shows performance measures of the NB algorithm using 10 cross-validations. These metrics are acquired from the confusion matrix of the NB classifier. The area Under ROC Curve is obtained from the ROC curve in figure 4.4.

Table 4.4. Performance measures of Naive Bayes classifier using 10 CV

Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
88.89%	0.7231	0.9273	0.7907	0.9189	0.9230	0.859

ID3 using 10 CV results

Figure 4.5 shows the ROC curve obtained for 10 cross-validation ID3 algorithms. The ROC curve is a graphical representation of the TPR against the false-positive rate obtained from the confusion matrix of ID3.

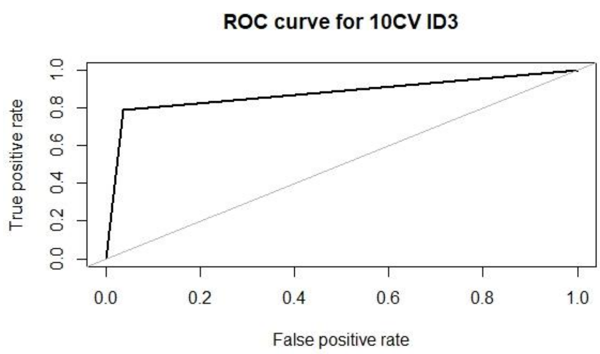

Figure 4.5. ROC curve for ID3 using 10 CV

Table 4.5 shows performance measures of the ID3 algorithm using 10 cross-validations. These performance measures are obtained from the confusion matrix of ID3. The area Under ROC Curve is acquired from the ROC curve in figure 4.5.

Table 4.5. Performance measures of ID3 using 10 CV

Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
91.5%	0.782	0.9636	0.7907	0.9217	0.9422	0.877

CART using 10 CV results

Figure 4.6 shows the ROC curve obtained for ten cross-validation CART algorithms. The ROC curve is a graphical representation of the TPR against the false-positive rate obtained from the confusion matrix of CART.

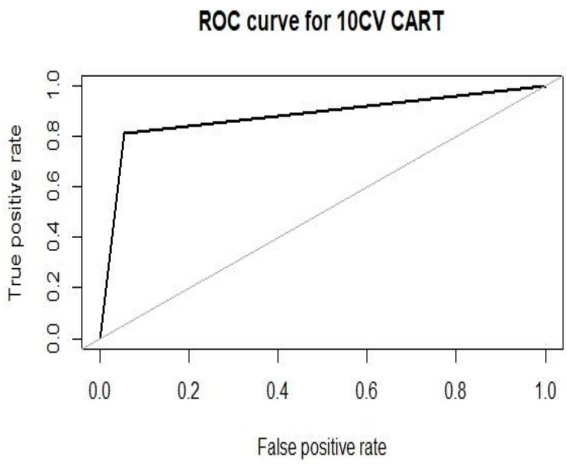

Figure 4.6. ROC curve for CART using 10 CV

Table 4.6 shows performance measures of the CART algorithm using 10 cross-validations. These performance measures are obtained from the confusion matrix of CART. The area Under ROC Curve is acquired from the ROC curve in figure 4.6.

Table 4.6. Performance measures of CART using 10 CV

Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
90.85%	0.7703	0.9455	0.8140	0.9286	0.9369	0.880

J48 using 10 CV results

Figure 4.7 shows the ROC curve obtained for 10 cross-validation J48 algorithms. The ROC curve is a graphical representation of the TPR against the false-positive rate obtained from the confusion matrix of J48.

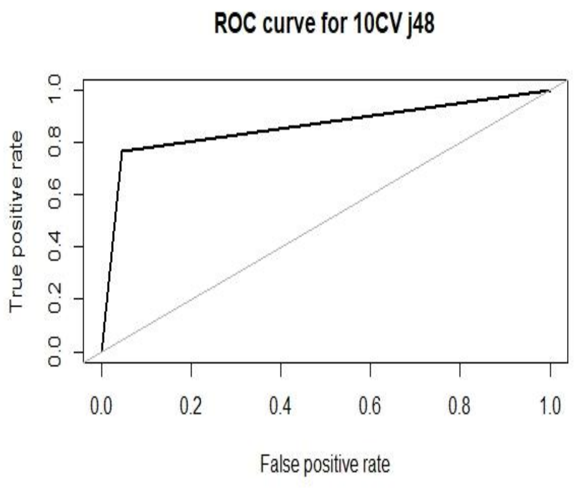

Figure 4.7. ROC curve for J48 using 10 CV

Table 4.7 shows performance measures of the J48 algorithm using 10 cross-validations. These metrics are acquired from the confusion matrix of J48. The area Under ROC Curve is acquired from the ROC curve in figure 4.7.

Table 4.7. Performance measures of J48 using 10 CV

Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
90.2%	0.7485	0.9545	0.7674	0.9130	0.9333	0.861

Gradient boosting using 10 CV results

Figure 4.8 shows the ROC curve obtained for 10 cross-validation gradient boosting algorithms. The ROC curve is a graphical representation of the TPR against the false-positive rate obtained from the confusion matrix of Gradient boosting.

Table 4.8 shows performance measures of the Gradient boosting algorithm using 10 cross-validations. These metrics are acquired from the confusion matrix of the Gradient boosting algorithm. The area Under ROC Curve is extracted from the ROC curve in figure 4.8.

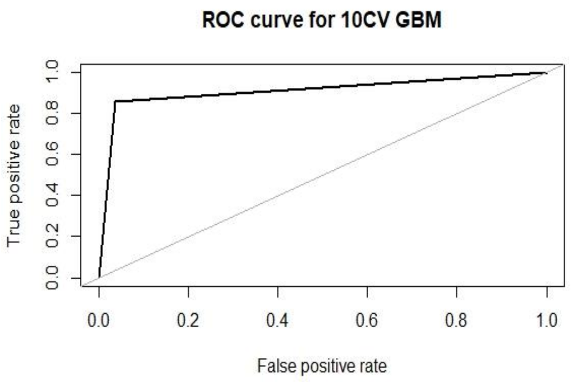

Figure 4.8. ROC curve for Gradient boosting using 10 CV

Table 4.8. Performance measures of angle boosting using 10 CV

Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC

93.46%	0.8359	0.9636	0.8605	0.9464	0.9549	0.912

4.2. Comparing Algorithms

Comparing results of algorithms using 10 CV

Table 4.9 shows all the performance measures obtained by implementing each algorithm. All the algorithms are implemented using 10 cross-validation techniques. In this table, a comparison of existing algorithms and the proposed algorithm is made. The proposed gradient boosting algorithm has obtained better performance measures.

Figure 4.9 illustrates the graph for comparing the accuracy of all the algorithms. Comparing the accuracy of 10 cross-validation techniques showed that Gradient boosting has obtained better accuracy.

By comparing the Accuracy, f-measure, and AUC of all the six existing algorithms using 10CV, ID3 showed the highest Accuracy, f-measure, and CART showed better AUC. Compare these results with the proposed algorithm results gradient boosting using 10CV. From the below graph in figure 4.10, it can be observed that Gradient boosting has obtained better AUC.

Table 4.9. Performance measures of all algorithms using 10 CV

Algorithm	Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
KNN	78.43%	0.4467	0.8727	0.5581	0.8348	0.8533	0.715
SVM	89.54%	0.7297	0.9545	0.7442	0.9052	0.9292	0.849
NB	88.89%	0.7231	0.9273	0.7907	0.9189	0.9230	0.859
ID3	91.5%	0.782	0.9636	0.7907	0.9217	0.9422	0.877
CART	90.85%	0.7703	0.9455	0.8140	0.9286	0.9369	0.880
J48	90.2%	0.7485	0.9545	0.7674	0.9130	0.9333	0.861
GBM	93.46%	0.8359	0.9636	0.8605	0.9464	0.9549	0.912

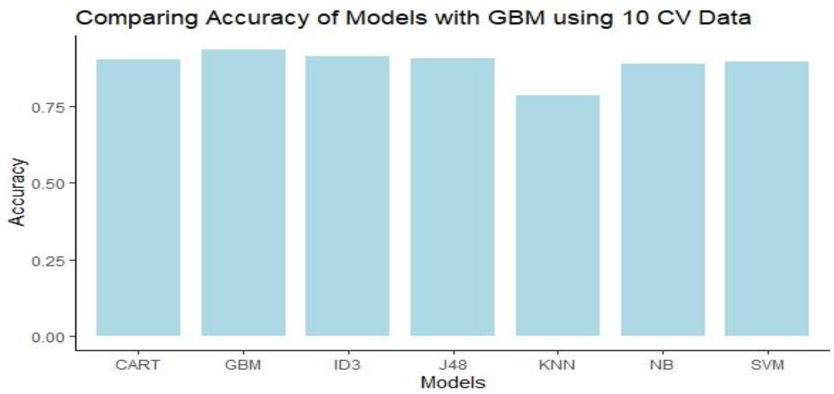

Figure 4.9. Comparing the accuracy of all algorithms using 10 CV

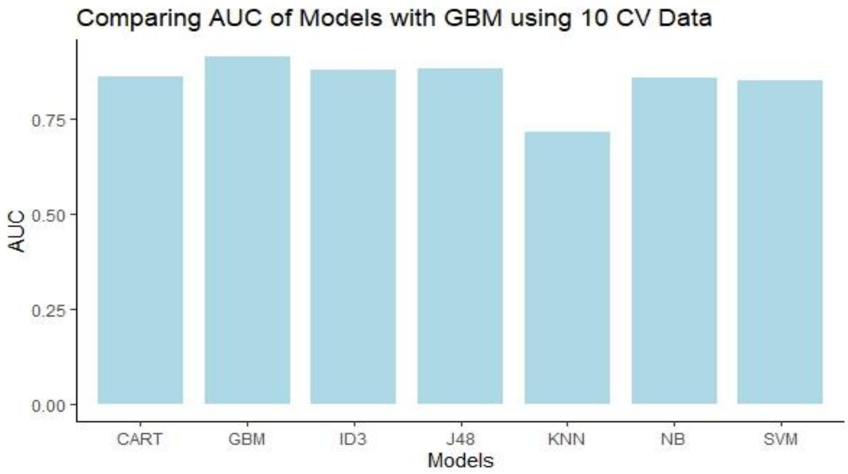

Figure 4.10. Comparing AUC of all algorithms using 10 CV

Comparing results of algorithms using 5 CV

Table 4.10 shows the values of all the performance measures obtained by implementing each algorithm. All the algorithms are implemented using 5 cross-validation techniques. In this table, a comparison of prevalent algorithms and the proposed algorithm is made. The proposed algorithm gradient boosting has obtained better performance measures.

Figure 4.11 illustrates the graph for comparing the accuracy of all the algorithms. Comparing the accuracies when 5 cross-validation technique is used shows that Gradient boosting has obtained better accuracy.

By comparing the Accuracy, f-measure, and AUC of all the six existing algorithms using 5CV, J48 showed the highest Accuracy, f-measure and AUC. Compare these results with the proposed algorithm gradient boosting using 5CV. From the below graph in figure 4.12, it can be observed that Gradient boosting has obtained better AUC.

Table 4.11. Performance measures of all algorithms using 5 CV

Algorithm	Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
KNN	77.83%	0.4743	0.8491	0.6197	0.8333	0.8411	0.703
SVM	90.43%	0.7649	0.9686	0.7606	0.9006	0.9333	0.865
NB	88.26%	0.726	0.9119	0.8169	0.9177	0.9148	0.864
ID3	91.3%	0.7914	0.9560	0.8169	0.9212	0.9382	0.886
CART	91.3%	0.793	0.9497	0.8310	0.9264	0.9378	0.890
J48	91.74%	0.8042	0.9497	0.8451	0.9321	0.9408	0.897
GBM	93.04%	0.8331	0.9686	0.8451	0.9333	0.9506	0.914

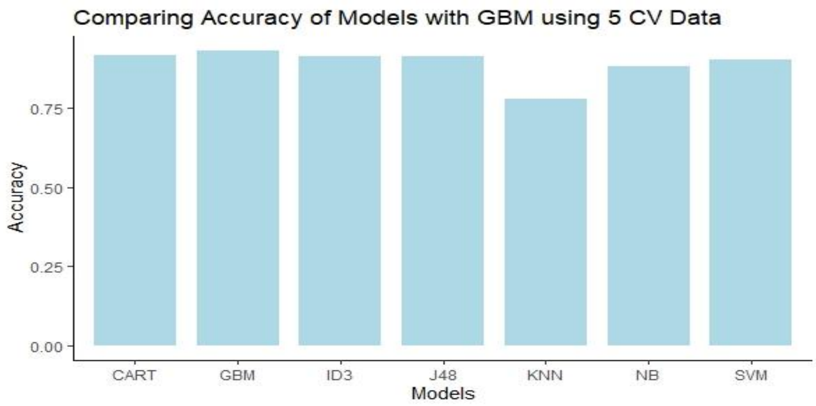

Figure 4.11. Comparing the accuracy of all algorithms using 5 CV

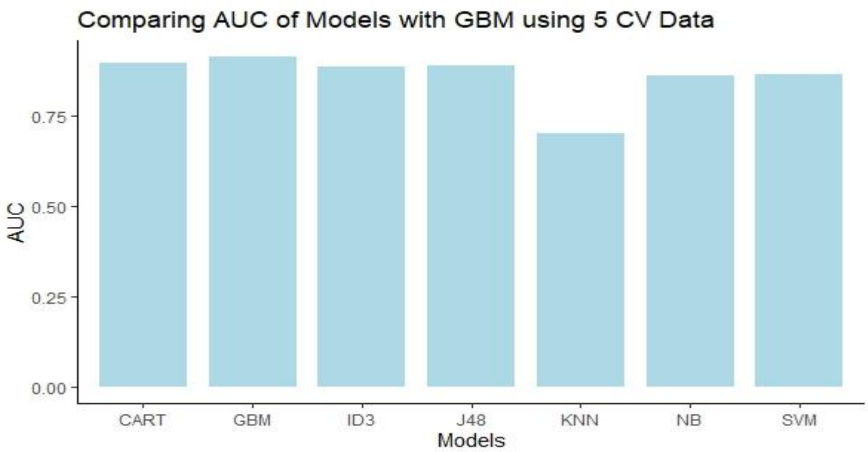

Figure 4.12. Comparing AUC of all algorithms using 5 CV

Comparing results of algorithms using 3 CV

Table 4.11 shows all the performance measures obtained by implementing each algorithm. All the algorithms are implemented using 3 cross-validation techniques. In this table, a comparison of existing algorithms and the proposed algorithm is made. The proposed algorithm gradient boosting has obtained better performance measures.

Figure 4.13 shows the plot for comparing the accuracy of all the algorithms. Comparing the accuracies when 3 cross-validation technique is used shows that Gradient boosting has obtained better accuracy.

Comparing the Accuracy, f-measure, and AUC of all the six existing algorithms using 3CV ID3 and CART showed the highest accuracy, and CART showed better AUC and f-measure. Compare these results with the proposed algorithm gradient boosting using 3CV. From the below graph in figure 4.14, it can be observed that Gradient boosting has obtained better AUC.

Table 4.11. Performance measures of all algorithms using 3 CV

Algorithm	Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
KNN	75.24%	0.4143	0.8381	0.5670	0.8073	0.8224	0.691
SVM	89.9%	0.7577	0.9571	0.7732	0.9013	0.9284	0.865
NB	88.27%	0.7302	0.9095	0.8247	0.9183	0.9138	0.809
ID3	92.51%	0.8242	0.9571	0.8557	0.9349	0.9458	0.906
CART	92.51%	0.8252	0.9524	0.8660	0.9390	0.9456	0.909
J48	92.18%	0.8171	0.9524	0.8557	0.9346	0.9433	0.907
GBM	94.14%	0.8605	0.9810	0.8557	0.9364	0.9581	0.926

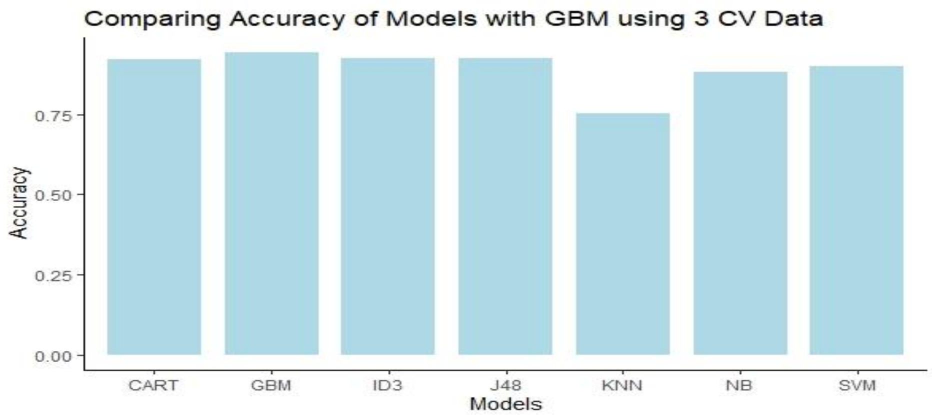

Figure 4.13. Comparing the accuracy of all algorithms using 3 CV

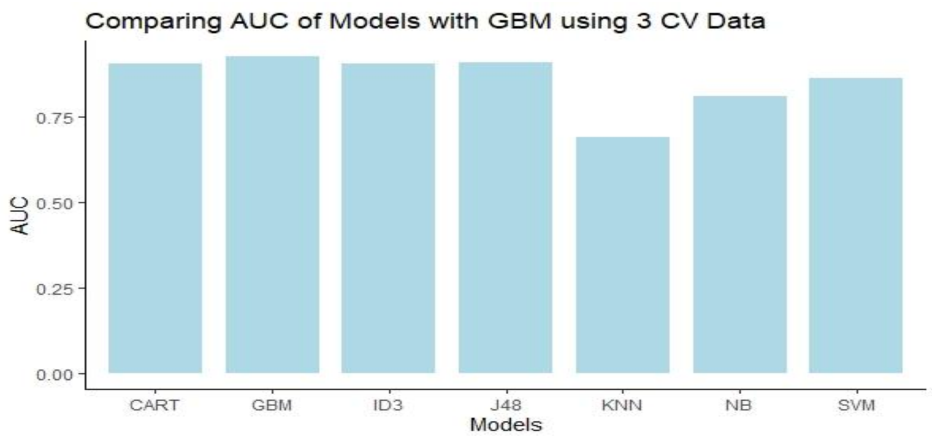

Figure 4.14. Comparing AUC of all algorithms using 3 CV

The ROC curve is shown only for algorithms implemented by applying 10-fold cross-validation. The performance measures for all algorithms with 3, 5 and 10 cross-validation are given above. By comparing the results of all algorithms of 10-fold cross-validation, it was observed that the Gradient boosting algorithm has the highest accuracy, kappa statistic, sensitivity, specificity, precision, f-measure and AUC with values 93.46%, 0.8359, 0.9636, 0.8605, 0.9404, 0.9549and 0.912 respectively. Similarly, from the results of 5 and 3 cross-validations,the gradient boosting algorithm obtains better performance measures.

4.3 Comparing ELM with GBM (Proposed Technique):

Extreme Learning Machine

ELM is a feed-forward neural network(NN)that could be used for classification. It contains one hidden layer, so a single hidden layer that feeds forward a neural network. The training of ELM is very fast compared to the artificial neural network. ELM has only a single input, hidden and output layers. It doesn't use a backpropagation algorithm like ANN. Instead, it utilizes an inverse matrix principle. It computes the output weight matrix using which the prediction is made. The stepwise algorithm for ELM is given below.

Algorithm 8: Extreme Learning Machine (ELM)

INPUT: Give the Dataset as input
OUTPUT: Predicted output values of input cases

ASSUMPTIONS: k is total records, $x_k$representsinput vector, h_t represents the output value for hidden neuron t and t = 1, 2,....,p, b_t is the bias for hidden neuron t, w_t represents weight vector for connections between the input layer and hidden layer neurons.t, β represents the weight vector connecting neurons of the hidden layer, and the output layer, g() is the activation function.

STEPS:

1. Start
2. Set values for the input layer neuron with the input instances.
3. Assign weights of input layer and biases for hidden layer neurons randomly.
4. Compute the output matrix for the hidden layer.

$$h_t = g(w_t * x_k + b_t), \text{where } k = 1,2, \ldots\ldots, n \quad (7)$$

$$H = \begin{bmatrix} g(w_l x_l + b_l) & \cdots & g(w_p x_l + b_p) \\ \vdots & \ddots & \vdots \\ g(w_l x_n + b_l) & \cdots & g(w_p x_n + b_p) \end{bmatrix} \quad (8)$$

5. Obtain output layer weight matrix, the pseudo inverse of H. Here D is the matrix containing actual target values from the input instances.

$$\beta = (H * H^T)^{-1} H * D \quad (9)$$

$$\beta = \begin{bmatrix} \beta_l \\ \vdots \\ \beta_p \end{bmatrix} \quad (10)$$

6. Calculate output for the input instances.

$$T = H * \beta \quad (11)$$

$$T = \begin{bmatrix} t_l \\ \vdots \\ t_p \end{bmatrix} \quad (12)$$

7. Return the predicted output values.
8. Stop

In 2^{nd}step, the values for the input neuron are assigned based on input records. Assigning the input layer weights and the hidden layer neurons bias with random values to is illustrated in step 3. In step 4, the output matrix for the hidden layer is computed. The general output function given in Formula (7) is utilized to calculate each element of matrix H in formula (8). The activation function in this step is generally a sigmoid function. The matrix H from this step is utilized to obtain the weight matrix for the output layer in step 5. Here formula (9) is for getting the output weight matrix, and formula (10) shows matrix representation. The matrices H and β from steps 4 and 5 are utilized to compute the output values in step 6. The formula (11) calculates the output matrix with predicted target values. Formula (12) gives the matrix representation of T. Lastly, and the predicted values are given as output for the given input instances from this matrix T.

Results obtained for ELM

ELM with 3-fold cross-validation is implemented on the Dataset, and the results are obtained.

ELM is compared with GBM 3-fold cross-validation is implemented on the Dataset, and the results obtained are tabulated in Table 4.12.

Table 4.12. Performance measures of ELM and GBM using 3 CV

Algorithm	Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
ELM	90.02%	0.7593	0.9568	0.7909	0.9211	0.9363	0.885
GBM - Proposed	94.14%	0.8605	0.9810	0.8557	0.9364	0.9581	0.926

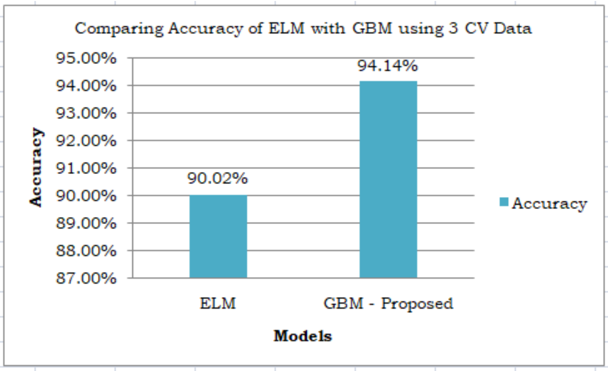

Figure 4.15. 3 CV Accuracy Comparison of ELM & GBM

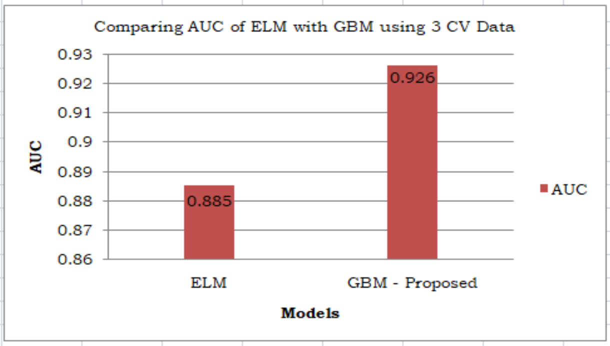

Figure 4.16. 3 CV AUCComparison of ELM & GBM

ELM is compared with GBM 5-fold cross-validation is implemented on the Dataset and the results obtained are tabulated in Table 4.13.

Table 4.13. Performance measures of ELM and GBM using 5 CV

Algorithm	Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
ELM	89.1%	0.7310	0.9417	0.7438	0.8819	0.9064	0.831
GBM - Proposed	93.04%	0.8331	0.9686	0.8451	0.9333	0.9506	0.914

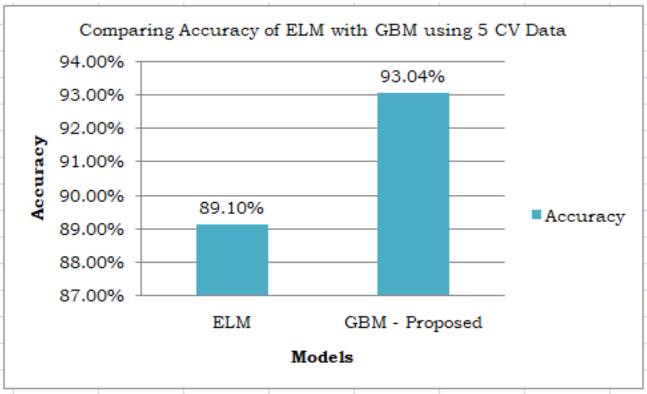

Figure 4.17. 5 CV Accuracy Comparison of ELM & GBM

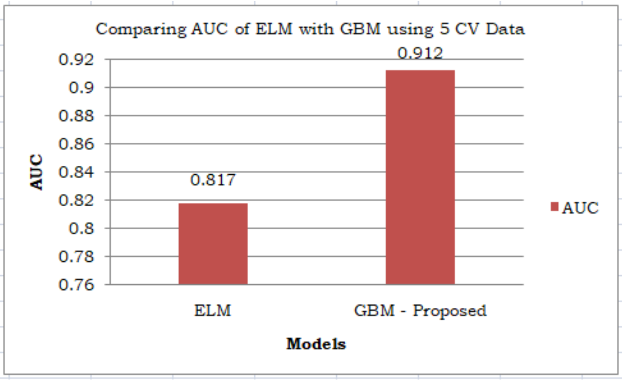

Figure 4.18. 5 CV AUCComparison of ELM & GBM

ELM is compared with GBM 10-fold cross-validation is implemented on the Dataset and the results obtained are tabulated in Table 4.14.

Table 4.14. Performance measures of ELM and GBM using 10 CV

Algorithm	Accuracy	Kappa	Sensitivity	Specificity	Precision	F-Measure	AUC
ELM	86.04%	0.7043	0.9108	0.7162	0.8716	0.8902	0.817
GBM - Proposed	93.46%	0.8359	0.9636	0.8605	0.9464	0.9549	0.912

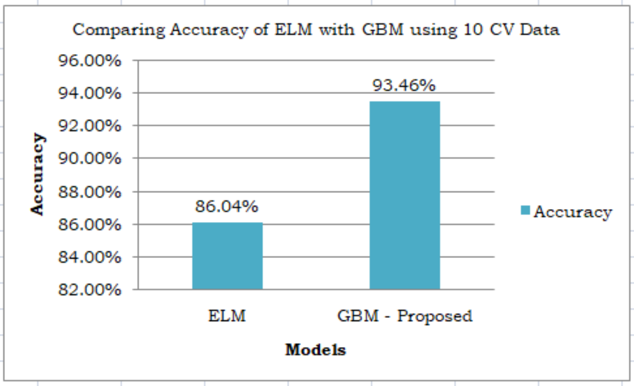

Figure 4.19. 10 CV Accuracy Comparison of ELM & GBM

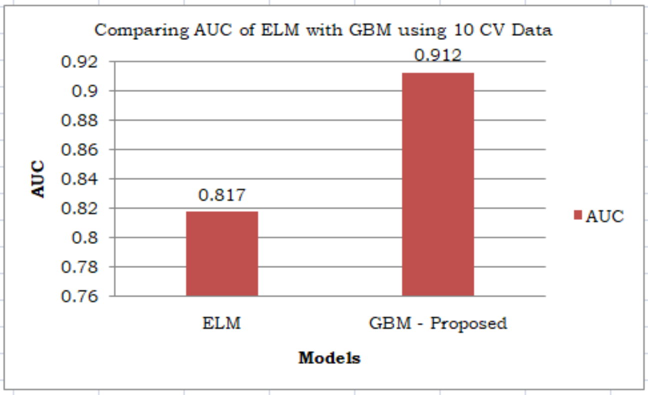

Figure 4.20. 10 CV AUCComparison of ELM & GBM

Tables 4.12, 4.13 and 4.14 show values of all the performance measures obtained by implementing each algorithm. All the algorithms are implemented using 3 cross-validation techniques, 5 cross-validation techniques, and 10 cross-validation techniques. In these tables, the comparison of existing algorithms and the proposed algorithm is made. The proposed algorithm gradient boosting has obtained better performance measures.

Figures 4.15, 4.17 and 4.19 show the plot for comparing the Accuracy of ELM with GBM. Figures 4.16, 4.18 and 4.20 show a plot for comparing the AUC of ELM with GBM. By comparing the accuracies when 3 cross-validations, 5 cross-validation techniques and 10 cross-validation techniques, it was observed that Gradient boosting had obtained better accuracy.

The accuracy, kappa statistic, sensitivity, specificity, precision, and f-measure are obtained using a function in the'caret' package called confusion matrix (). The ROC curve and AUC for true and false positive rates are obtained using the roc. curve() function in the'ROSE' package. In chapter 5, the conclusion is provided

5. Conclusion

A model to predict gestational diabetes in pregnant women is developed in this work. Several existing classification algorithms were implemented in R programming, like the NB classifier, SVM, KNN, ID3, CART and J48. The proposed algorithms Gradient boosting machine (GBM) and ELMarewere also implemented. K-fold cross-validation is applied with different values of k as 3, 5 and 10. Comparing the advanced ML technique ELM with the Gradient boosting machine proves that the proposed GBM obtained better results. Hence, it is concluded that GBM works better than other advanced techniques for the considered Dataset for gestational diabetes. The results showed that the Gradient boosting algorithm performs better than different algorithms. The Gradient boosting algorithm obtained better values of Accuracy and AUC of 94.14% and 0.926, respectively, when 3 cross-validations were applied. In the future, even better results can be obtained by using neural networks or deep neural networks.

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