Biomedical
Communication

BBRC
Bioscience Biotechnology
Research Communications

Biosc.Biotech.Res.Comm. Vol 14 No (1) Jan-Feb-March 2021 Pp 74-82

Performance Assessment of Different Machine Learning Algorithms in Predicting Diabetes Mellitus

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ABSTRACT

Diabetes Mellitus (DM) is considered as a heretical metabolic disorder and widely spread long standing slow poison which poses a great threat to human health. Faster and accurate prediction of diabetes is a dire need and Machine Learning (ML) can play a pivotal role in terms of enhancing medical health technology and develop an e-healthcare system. In this regard, ten ML algorithms have been studied comprehensively and they are implemented by Jupyter Notebook. Hence, the ML models are trained with the dataset of Kaggle machine learning data repository of Frankfurt hospital, Germany. Effective data processing method is proposed using 5-fold cross validation method to achieve stable accuracy. However, hyper-parameter tuning technique is employed with a view to achieving better performance from the ML models. After rigorous simulation, Gaussian Process (GP) emerged as the best performing algorithm which is proposed as the most efficient classifier with an accuracy of 98.25%. However, Random Forest (RF) and Artificial Neural Network (ANN) displayed accuracy of 97.25% and 96.5% respectively which are quite satisfactory. Hence, the performances of the ML models are assessed with different metrics like Accuracy, Sensitivity, Precision, F1-score, Specificity and ROC_AUC and thus, a comparative analysis among all the ML models are portrayed graphically. Efficient prediction of Diabetes by ML algorithms can significantly contribute in decreasing the annual mortality rate specially in developing countries like Bangladesh. Therefore, this study can meaningfully assist the healthcare professionals in the process of proper and faster treatment of Diabetes Mellitus and thus, an efficient e-healthcare system can be established in future.

KEY WORDS: DIABETES MELLITUS, MACHINE LEARNING (ML), CROSS VALIDATION, HYPER-PARAMETER TUNING, E-HEALTHCARE.

INTRODUCTION

Diabetes mellitus (DM) is considered as a cluster of metabolic disorders and appears to be a common disease among mass people nowadays imposing a lot of complications in human body. Insulin Dependent Diabetes Mellitus (IDDM) or Type-1 diabetes is witnessed among children because of the genetic disorders where the body fails to produce adequate insulin. However, 'Type 2' diabetes is normally observed in middle-aged people for most cases where body is not able to use the insulin produced inside or it fails to produce adequate insulin or both and it is termed as "Non-Insulin-Dependent Diabetes Mellitus" (NIDDM). On the other hand, gestational diabetes is commonly seen among 2-10% pregnant women where they may not have diabetes prior to pregnancy or can develop 'Type 2' diabetes after the pregnancy (Lee et al., 2018).

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Received 05/12/2020 Accepted after revision 21/03/2021
Published: 31st March 2021 Pp- 74-82

Available at: https://bbrc.in/ DOI: http://dx.doi.org/10.21786/bbrc/14.1/10

However, Diabetes Mellitus (DM) is affected by various factors like pregnancies, blood pressure, glucose, skin thickness, BMI, diabetes pedigree function, age but amongst all, the prime reason is blood sugar level. If diabetes remains untreated and unidentified many complications occur, for instance, various organs like eyes, teeth, legs, tiny blood vessels, kidneys, liver, heart and nerves get affected which results in various acute and chronic diseases in course of time (Yoon et al., 2017). In 2019, WHO estimates that worldwide 463 million people have diabetes with 'Type 2' diabetes making up about 90% of the cases and the number of cases may increase to 642 million by 2040. Rates are alike in women and men and this disease leads to a person's risk of early death. The WHO also states that approximately 4.2 million deaths occurred in 2019 due to diabetes and globally it is the 7th leading cause of death (Saeedi et al., 2020).

In Bangladesh, most of the people are not aware of deadly clutch of diabetes which becomes rampant in course of time. Therefore, early detection can pave the way to ensure better treatment for the patients and assist the healthcare professionals in this regard.Machine learning algorithms are being employed in different times by many researchers in predicting diabetes. A hybrid Neural Network System was developed by implementing Artificial Neural Network (ANN) and Fuzzy Neural Network (FNN) for diabetes diagnosis and an accuracy of 84.2% was attained (Kahramanli and Allahverdi, 2008). On the other hand, an approach was proposed that combining the Least Square Support Vector Machine (LS-SVM) classifier with Generalized Discriminant Analysis (GDA) improves the accuracy of diabetes classification, (Polat et al., 2008).

Here, the GDA technique was used for feature reduction and then LS-SVM was applied for modeling. Using 10-fold cross validation, this combination of two methods depicted 82.05% accuracy. However, a classification system is manufactured for diabetes using the Bayes' network, obtaining an accuracy rate of 72.3% (Guo et al., 2012). Again, a research is conducted on diabetes prediction exploiting real-time dataset and different ML models are implemented (Meng et al., 2013). This study achieved its highest accuracy of 77.87% for the decision tree model (C5.0), 76.13% of accuracy in regression model and 73.23% in ANN model. Furthermore, a hybrid method was implemented utilizing NSGA-II technique for diabetes detection and 86.13% accuracy was obtained (Zangooei et al., 2014). On the other hand, a unique system is designed for diabetes classification employing an adaptive network-based fuzzy inference system and 82.3% accuracy was obtained (Sagir and Sathasivam, 2017).

It is observed that the above-mentioned researches contributed in employing various ML techniques in predicting diabetes but none of them came up with an accuracy more than 90%. So, with the advancement of modern technology, ML algorithms hold the promise to assist in providing more accurate predictions and satisfactory results than current practices which leverage the healthcare system and save healthcare expenditures. The key objective of this study is to develop ML models and investigate their performances to predict diabetes with promising outcomes. As it is seen that achieving higher accuracy is always a challenge for the ML researchers. In this regard, a good diabetes dataset is explored and promising outcomes are observed with the assistance of ML algorithms.

Hence, several machine learning algorithms are studied extensively such as Logistics Regression (LR), K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Naive Bayes (NB), Adaboost (AdB), Random Forest (RF), Stochastic Gradient Descent (SGD), Gradient Boosting (GB), Gaussian Process (GP) and Artificial Neural Network (ANN) and an investigative and comparative analysis is portrayed in the forthcoming sections. The performance metrics of different algorithms were explored by various standards, such as accuracy, sensitivity, precision, F1-score, specificity and ROC_AUC. Therefore, this kind of comprehensive analysis among all the ML models with diabetes dataset will shape the way of developing a computer-aided healthcare system which is direly needed specially in developing countries like Bangladesh.

MATERIAL AND METHODS

Data Preprocessing: The proposed approach consists of three basic steps. Firstly, the Kaggle dataset was loaded into pandas for data preprocessing (Kaggle Diabetes Dataset, Frankfurt hospital, Germany). However, further data preprocessing is accomplished on the proposed dataset with 5-fold cross validation. Secondly, the preprocessed dataset is fitted into our proposed ten different machine learning models with hyper parameter tuning. Lastly, the models are tested and various performance metrics like accuracy, precision, sensitivity, specificity, F1 score and ROC_AUC are evaluated and overall comparative analysis is carried out. In this work, this dataset of diabetes has been taken from the hospital Frankfurt, Germany. The data set contains 2000 instances of observations of patients consisting of 9 attributes with no missing values. In this work, 1600 samples are selected as training set and 400 samples chosen for test set. The details of the attributes of the dataset is depicted in Table 1.

From the dataset, it is observed that some attributes like glucose, blood pressure, skin thickness, insulin and BMI have zero value but this is not possible practically. So, those are treated as missing data and they are replaced by the mean value of the specific attribute column having the missing value. From the Table 1, it is evident that some of the values of attributes of the dataset are not on the same scale which might have caused some issues in the machine learning models. As lots of the machine learning models are based on Euclidean distance, the higher range attributes dominated the lower range attributes. Therefore, the entire attribute should be in same scale. Some observations of scaled attributes are shown in Table 2.

Study of Machine Learning Algorithms: The machine-learning algorithms used in this paper are briefly described below:

Logistics Regression (LR): Logistic Regression (LR), a widely used model in machine learning, utilizes a logistic function to classify a binary dependent variable over one or more independent variables or features (Maniruzzaman et al., 2019). The main advantages of this type of supervised machine learning algorithms are that it can handle nonlinearity and it is easy to implement and very efficient to train. Combining linear regression line and sigmoid function, the best fitting curve can be attained for dataset. The following equations are used in this process:

Linear Regression Function: $y = b_0 + b_1 * x$

Sigmoid/Logistic Function: $p = \frac{1}{1+e^{-y}}$

Logistic Regression Function: $\log it(p) = \ln\left(\frac{p}{1-p}\right) = b_0 + b_1 * x$

Where, p is the dichotomous (binary) output which is the result of weighted sum of input features x. If the probabilistic output is more than 0.5 line, the output is 1 otherwise the output is 0.

Naive Bayes (NB): Based on the Bayes' Theorem, Naïve Bayes is appointed extensively in various classification problems (Balaji et al., 2020). This classifier is a probabilistic machine learning algorithm that can be implemented simply and the predictions made in real-time are quick and space efficient.
Bayes' theorem:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

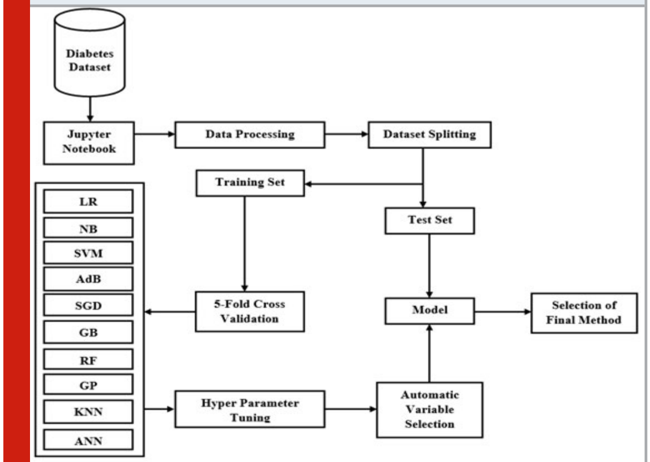
Table 1. The attributes of dataset

No	Attribute	Description	Range of value	Type
1	Pregnancies	How many times	0 - 17	Numeric
2	Glucose	Glucose value	0 - 199	Numeric
3	Blood Pressure	Blood Pressure level	0 - 122	Numeric
4	Skin Thickness	Skin Thickness value	0 - 110	Numeric
5	Insulin	Insulin Level	0 - 744	Numeric
6	BMI	Mass	0 – 80.6	Numeric
7	Diabetes Pedigree Function	Family History	0.08 – 2.42	Numeric
8	Age	Age of diabetic patient	21 - 81	Numeric
9	Outcome	Binary (Yes or No)	0 - 1	Nominal

Table 2. Observation of preprocessed scaled dataset

No	Pregnancies	Glucose	Blood Pressure	Skin Thickness	Insulin	BMI	Diabetes	Age Pedigree Function
1	2.540	-0.014	0.466	-0.233	-0.715	-0.701	-0.650	2.507
2	4.065	1.293	0.160	1.243	0.294	1.044	1.043	1.211
3	-0.814	-0.606	0.262	-1.280	-0.715	0.874	-0.547	0.780
4	-0.204	-0.201	-0.144	1.120	0.525	0.704	-0.981	-0.428
5	1.625	1.324	0.466	-1.280	-0.715	0.062	-0.987	1.039

Figure 1: Proposed workflow diagram



Where,
P(A|B) = Probability of B occurring given event A has already occurred.

P(B|A) = Probability of A occurring given event B has already occurred.

P(A) = Probability of event A occurring.

P(B) = Probability of event B occurring.

Let, 'X' is a new data point, found P(A|X) and P(B|X). Then our classifier compares those two and decides X belongs to 'A' or 'B'.

Support Vector Machine (SVM): Support Vector Machine, a commonly used classification technique which aims to classify data points by an appropriate hyper plane in a multidimensional space. The decision boundary line or the hyper plane is drawn, maintaining the maximum margin from the support vectors. SVM works proficiently as there is a margin of separation between classes and also more effective in high dimensional spaces. When dataset is not linearly separable mapping to a higher dimension to make the dataset linearly separable, nonlinear functions are used as kernel. So, polynomial kernel is applied as the hyper plane to get more accuracy and less over fitting than linear kernel (Djelloul and Amir, 2019).

For degree-d polynomials, the polynomial kernel is defined as,

$$K(x,y) = \left(x^T y + c\right)^d$$

Where x and y are points in our dataset and c stands for the homogeneity of our function.

Adaboost (AdB): Amongst Machine Learning algorithms, Boosting is an ensemble learning method used to improve the prediction power. AdaBoost (Adaptive Boosting) is a sequential learning process where multiple decision tree models are used as weak learners (Li et al., 2019). All the models do not have equal weight for the final model. The hypothesis is obtained for each subset of the dataset and then combined to get a single better hypothesis. The compensation is done by varying the weights of data. AdaBoost is sensitive to noisy data. The final equation for classification can be represented as,

$$F(x) = sign\left(\sum_{m=1}^{M} \theta_m f_m(x)\right)$$

Where, f_m stands for the m^{th} weak classifier and θ_m is the corresponding weight.

Stochastic Gradient Descent (SGD): Stochastic Gradient Descent (SGD) refers to descending of a slope to reach the lowest point called global minima on the structure by minimizing the cost function to update the weights (Talo et al., 2019). The equations used for Gradient descent:

Updated weights, $\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right) x_j^{(i)}$

Cost function, $j(\theta) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$

m = number of examples

$h_\theta(x^{(i)})$ = hypothesis function

$y^{(i)}$ =Actual output

$x_j^{(i)}$ = Input

α = Learning rate; Range (0 to 1)

The main difference between Gradient Descent (GD) and Stochastic Gradient Descent is that the whole training data per epoch is used in GD whereas, in SGD, only single training example per epoch are employed to fine-tune the weight. Stochastic Gradient Descent helps to find overall global minima which is a faster process than Gradient Descent.

Gradient Boosting (GB): Gradient Boosting technique refers to technique where a prediction model is constructed in the form of an ensemble of weak prediction models, typically decision trees. The Gradient Boosting, an ensemble learning algorithm works on the principle of gradient decent (Chen et al., 2018). A base (weak) model is created and learned by optimizing the loss function. We are boosting base model with the help of sequentially adding several DT models, where we took last model's residual value as next models predicted value to reduce the overall error. And with the help of learning rate (α) we reduce over fitting.

Random Forest (RF): In Machine Learning Bagging is an Ensemble Learning used to improve the prediction power (Javeed et al., 2019). Random Forest method which combines a lot of Decision Tree method and combines the idea of bagging and the random selection of features for each one of the trees from our dataset as a subset together. Taking the majority vote from the trees and deciding the classification based on that. And that power of numbers can help get rid of certain errors and certain uncertainties in our algorithm and make it more precise and one of the best learning algorithms. One of the major pros is that it can handle a huge amount of data proficiently.

Gaussian Process (GP): Gaussian process (GP), a nonparametric classification method is founded on Laplace approximation and Bayesian' methodology (Lang et al., 2019). For approximating the non-Gaussian posterior by a Gaussian, Laplace approximation is used. Bayesian' methodology undertakes some preceding distribution on the basic probability densities that promises some smoothness properties. Gaussian Process are a type of Kernel method, like SVMs, although they are able to predict highly calibrated probabilities, unlike SVMs. Hence it is a very effective classifier.

K-Nearest Neighbors (KNN): K-nearest neighbors (KNN) is one of the simplest supervised machine learning algorithms that can be deployed for both classification and regression analysis. KNN assumes the nearest data points in the feature space. It is based on feature similarity and classifies a data point based on how its neighbors are classified (Hossain et al., 2019). It uses Euclidean distance calculation to find the nearest data point (neighbor). The K-nearest neighbors of the new data point, according to the straight-line distance (also called the Euclidean distance) is a popular and familiar choice.

Where, Euclidean Distance= $\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$

Artificial Neural Network (ANN): Artificial Neural Network (ANN) is an advanced method that mimics the human brain holding a notable promise in pattern recognition of huge datasets (Nasser and Abu-Naser, 2019). Here, layers of neurons are constituted which acts as the fundamental processing unit. Firstly, input layer is placed that takes the inputs from the dataset. Then, the output layer forecasts final outcome. However, the hidden layers stay between these two layers, which accomplishes most of the calculation compulsory for the network. Hence, the forward and backpropagation method are implemented iteratively and the cost functions are evaluated each time. The output of this layer is fed to the next layer and by this manner the data is propagated through the network and this is called Forward Propagation.

Then the cost function is calculated by actual output and the predicted output and back propagated through the network. This cycle of forward propagation and back propagation is iteratively performed with multiple inputs. This process continues until our weights are adjusted such that the network can predict the classification correctly. Some prime application of ANN is facial recognition, forecasting, music composition etc. In this paper, ANN is used as binary classifier. So, the same hypothesis function used in Logistic Regression is brought into action.

$h_\theta(x) = \frac{1}{1+e^{-\theta^T x}}$ Where, θ^T = Transpose of weight matrix for a layer.

The network actually learns through Back propagation algorithm as,

$$\partial_j^{(l)} = \frac{\partial(\cos t(i))}{\partial z_j^{(l)}} \qquad \text{for, } j \geq 0$$

Where, for i^{th} sample,

$$\cos t(i) = y^{(i)} \log h_\theta\left(x^{(i)}\right) + \left(1 - y^{(i)}\right) \log h_\theta\left(x^{(i)}\right)$$

RESULTS AND DISCUSSION

After studying ten supervised machine learning techniques, they are implemented for the classification of diabetes disease samples and satisfactory performances are witnessed from the ML models. The corresponding confusion matrices are presented in Table 3.

Table 3. Confusion Matrices of all ML models

Confusion Matrix		Predicted	
(LR)		True	False
Actual	True	243	29
	False	59	69

Confusion Matrix		Predicted	
(NB)		True	False
Actual	True	230	42
	False	55	73

Confusion Matrix		Predicted	
(SVM)		True	False
Actual	True	271	1
	False	62	66

Confusion Matrix		Predicted	
(AdB)		True	False
Actual	True	237	35
	False	50	78

Confusion Matrix		Predicted	
(SGD)		True	False
Actual	True	210	62
	False	44	84

Confusion Matrix		Predicted	
(GB)		True	False
Actual	True	266	6
	False	8	120

Confusion Matrix		Predicted	
(RF)		True	False
Actual	True	266	6
	False	5	123

Confusion Matrix (GP)		Predicted	
		True	False
Actual	True	269	3
	False	4	124

Confusion Matrix (KNN)		Predicted	
		True	False
Actual	True	257	15
	False	33	95

Confusion Matrix (ANN)		Predicted	
		True	False
Actual	True	265	7
	False	7	121

The actual comparison among the studied ML models is evident from Table 4 based on various performance metrics like Accuracy, Sensitivity, Specificity, F1 score and ROC_AUC. All these metrics can be achieved with the assistance of confusion matrix. With the tuned configuration, Gaussian Process (GP) depicted the highest accuracy (98.25%) whereas the overall accuracy is above 75%. Besides Gaussian Process (GP), satisfactory accuracy is also witnessed in other algorithms like RF (97.25%), ANN (96.75%) and GB (96.50%).

Figure 2: ROC of all the ML models

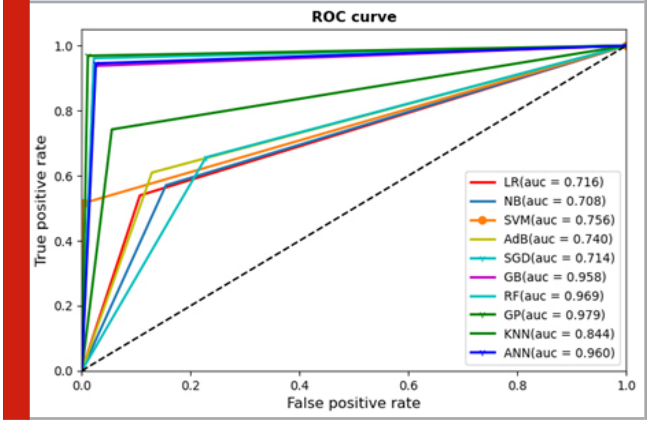


Table 4. Performance metrics of all ML models

Name of the algorithm	Accuracy (%)	Precision	Sensitivity	Specificity	F1 Score	ROC_-AUC
LR	78.00	0.704	0.539	0.893	0.610	0.716
NB	75.75	0.634	0.570	0.845	0.600	0.708
SVM	84.25	0.985	0.515	0.996	0.676	0.756
AdB	78.75	0.690	0.609	0.871	0.647	0.740
SGD	76.50	0.713	0.445	0.915	0.548	0.710
GB	96.49	0.952	0.937	0.976	0.944	0.958
RF	97.25	0.953	0.960	0.977	0.957	0.969
GP	98.25	0.976	0.968	0.988	0.972	0.979
KNN	88.00	0.863	0.742	0.944	0.798	0.844
ANN	96.75	0.932	0.969	0.967	0.950	0.968

Table 5. Performance Assessment of ML Models

Serial No.	Accuracy	Precision	Sensitivity	Specificity	F1 Score	ROC-AUC
1.	GP (98.25%)	SVM (0.985)	ANN (0.969)	SVM (0.996)	GP (0.972)	GP (0.979)
2.	RF (97.25%)	GP (0.976)	GP (0.968)	GP (0.988)	RF (0.957)	RF (0.969)
3.	ANN (96.75%)	RF (0.953)	RF (0.960)	RF (0.977)	ANN (0.950)	ANN (0.968)

Figure 3: Comparison of accuracy among all the ML models

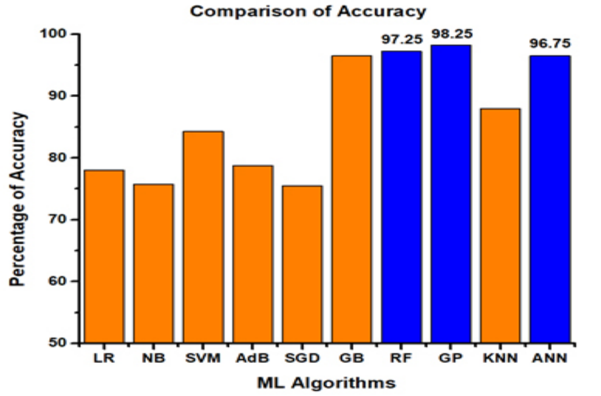


Figure 4: Comparison of precision among all the ML models

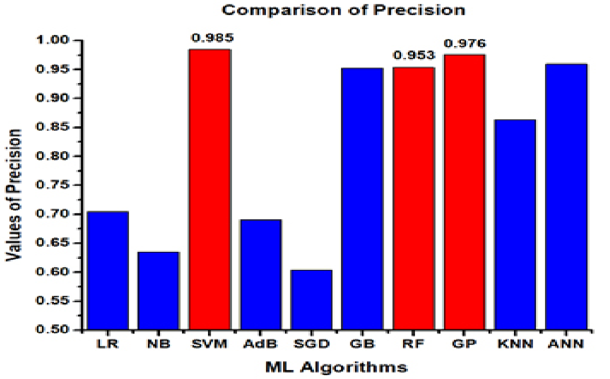
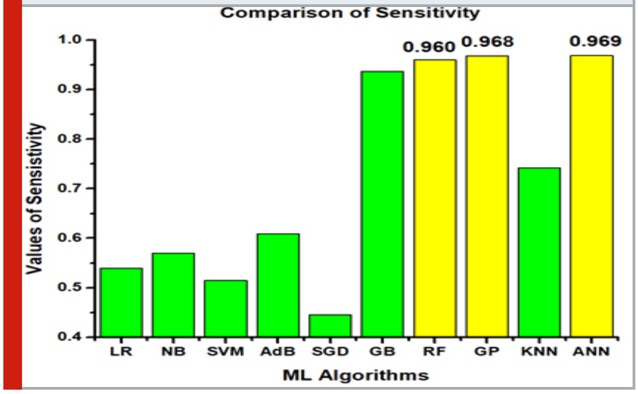


Figure 5: Comparison of sensitivity among all the ML models



The dataset, being imbalanced, some machine learning algorithms can get biased and still gives higher accuracy. So, different performance metrics like accuracy, sensitivity, precision, specificity, F1-Score and ROC_AUC are investigated so that the ML models can be evaluated more comprehensively. Table 5 represents the best performing algorithms considering different performance parameters. Amongst them, the best ML model is Gaussian Process (GP) as it contains least amount of over fitting, fast and accurate prediction. The other nearly performed models are GB, RF and ANN. It is also observed that these algorithms showcased better accuracy in comparison with other literature studied.

Figure 6: Comparison of specificity among all the ML models

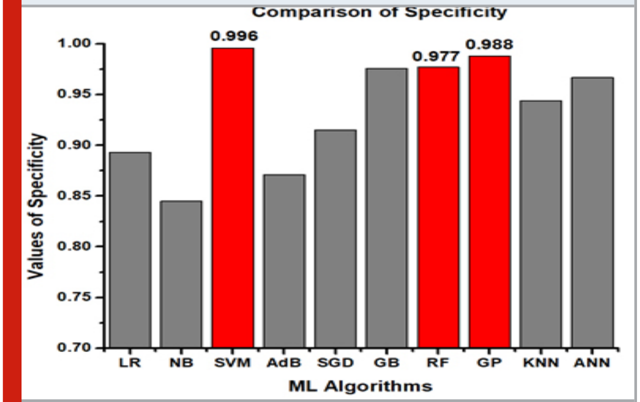


Figure 7: Comparison of F1 Score among all the ML models

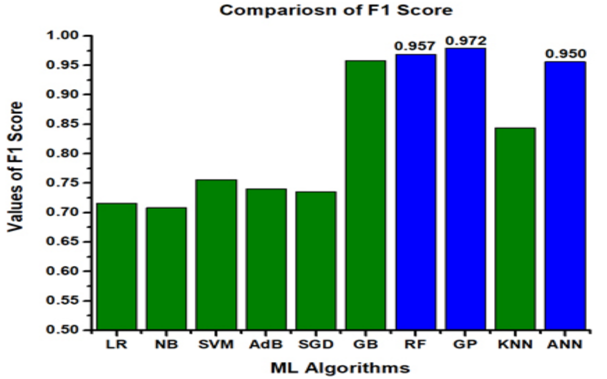
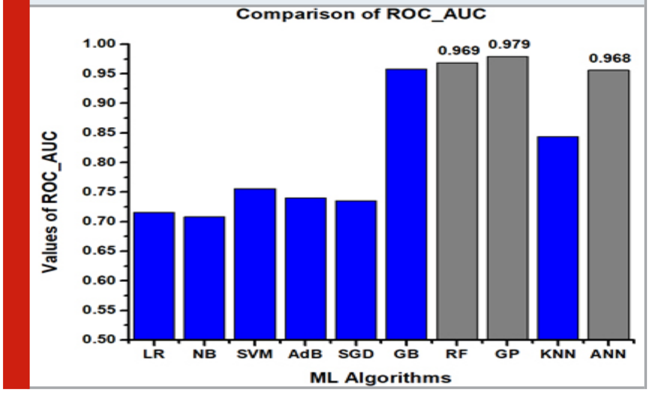


Figure 8: Comparison of ROC_AUC among all the ML models



The comparative analyses among all the ML models in terms of accuracy, precision, sensitivity, specificity, F1 score and ROC_AUC are presented graphically in Figure 3, Figure 4, Figure 5, Figure 6, Figure 7 and Figure 8 respectively.

CONCLUSION

In our proposed work, different machine learning algorithms are compared and analyzed based on various performance evaluation techniques like accuracy, sensitivity, precision, F1-score, Specificity and ROC_AUC. The obtained classification results demonstrate that the machine learning method Gaussian Process (GP) gives more accurate prediction and better performance than other methods discussed in this study. Still, some of the other methods used in this study such as Gradient Boosting (GB), Random Forest (RF) and Artificial Neural Network (ANN) provide exemplary results compared to other studies available in the existing literature. The primary goal of this study is to be a supportive element for doctors to arrive at a precise treatment routine for their patients suffering from diabetes. Because of great accuracy and fast processing time, this study can open a window in developing e-healthcare system for the diabetic patients. In future, more algorithms will be explored in different datasets so that more insights can be achieved and more information can be stored which will enable the healthcare professionals to utilize computer-aided diagnosis as an efficient tool in the process of faster and proper treatment for diabetic patients.

Conflict of Interest: Authors have no conflict of interest.

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