Journal of Computer Science
https://dergipark.org.tr/en/pub/bbd
Anatolian Science

ISSN,e-ISSN: 2548-1304
Volume:10, Issue:1, pp:33-42, 2025
https://doi.org/10.53070/bbd.1632130
Research Paper

The Role of Machine Learning Models in Early Diabetes Diagnosis: A Dataset Based Analysis

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Received:Feb.03, 2025 Accepted:Feb.20,2025 Published:Jun.1,2025

Abstract— Diabetes is a chronic metabolic disease in which the level of glucose in the blood rises above normal. The main reason for this is that the pancreas cannot produce enough insulin, or the insulin produced cannot be used effectively. For diabetes to be managed and complications to be avoided, early diagnosis is essential. Advanced technologies such as machine learning contribute to both individual health management and public health systems by providing high accuracy rates in early diagnosis. In this study, it is aimed to examine the role of machine learning methods in the early diagnosis of diabetes. For this purpose, the methods were analyzed on two different datasets. Support Vector Machines (SVM), Decision Trees (DT), and Artificial Neural Networks (ANN) were among the machine learning classifiers that were employed. In both datasets, the performance of the models in terms of metrics such as accuracy, sensitivity, and specificity were evaluated and compared. According to the results, the Bagged Trees algorithm showed the best performance with 96.2% in the first dataset we used, BIT Mesra Dataset. In the Pima Indian dataset, the SVM algorithm achieved an accuracy rate of 77.2%. The study provides a method for early diagnosis of diabetes, and emphasizes the importance of data diversity in this field.

Keywords: *Diabetes, Machine Learning, BIT Mesra Dataset, Pima Indian Dataset, Artificial Intelligence.*

1. Introduction

Diabetes mellitus, also known as diabetes mellitus, is a chronic metabolic disorder that results from an inability to stabilize the glucose level in the blood. This condition occurs due to insufficient release or ineffective use of the hormone insulin. Genetics such as hereditary genetics, obesity, bad food, and physical inactivity have a vital influence on the development of diabetes. Although diabetes manifests itself with symptoms such as thirst, polyuria, polydipsia, blurred vision, and weight loss, it leads to serious complications such as cardiovascular diseases, nephropathy, neuropathy, and diabetic retinopathy in the long term (Arıkoğlu and Kaya, 2015).

Diabetes is characterized as a ‘silent killer’, and it is stated that this disease significantly reduces the quality of life of individuals (Todkar, 2016). Diabetes is increasing rapidly worldwide. The number of individuals with diabetes, which was approximately 171 million in 2000, was estimated to reach 366 million in 2030. However, 2021 data show that these estimates have been exceeded and diabetes is spreading much faster. In the case of Turkey, it has been reported that the number of people with diabetes, which was 2.9 million in 2000, reached approximately 7 million in 2023. Turkey is among the countries with the fastest increase in diabetes in Europe, which increases the importance of early diagnosis and treatment measures (Önsöz and Topuzoğlu, 2018).

To avoid long-term consequences and enhance people's quality of life, diabetes must be diagnosed early. Artificial intelligence and machine learning methods offer promising results in the early diagnosis of diabetes and bring a new dimension to the studies in this field. There are many studies on early diagnosis of diabetes in the literature.

A total of 520 samples, 200 of which were negative and 320 of which were positive, were utilized by Akyol and Karacı for diabetes binary classification using a dataset with 16 features (Akyol and Karacı, 2021). Classifiers such as Random Forest, Gradient Boosting, K-Nearest Neighbour were performed on the dataset. The voting ensemble classifier provided the highest performance, with an average classification accuracy of 97.31% in the validation experiment.

By organizing the information gathered from 70000 medical records of patients in 130 hospitals in the United States, Başer et al. sought to categorize people based on their diabetes state (Başer et al., 2021). Classification was done using machine learning methods that were appropriate for the data set. According to the results obtained, the best correct classification performance in the relevant dataset was obtained with the Random forest algorithm.

Tigga and Garg estimated the risk of Type 2 diabetes using different machine learning algorithms. Once the model is trained, individuals can self-assess their diabetes risk. To run the experiment, samples were collected with questions about health, lifestyle and family history. The algorithms were also applied to the Pima Indian Diabetes database and the highest accuracy in both datasets was 0.75 with the Random Forest Classifier (Tigga and Garg, 2020).

Modak and Jha used a set of machine learning techniques to predict diabetes using a real dataset from Kaggle. Among the ensemble techniques tested, CatBoost offered the highest performance with an accuracy of 95.4% (Modak and Jha, 2023).

To identify diabetes early on, Sisodia and Sisodia employed three machine learning algorithms: Decision Tree, SVM, and Naive Bayes. Among the classifications performed with the Pima Indians Diabetes Database (PIDD), Naive Bayes showed the highest accuracy with 76.30% compared to other algorithms (Sisodia and Sisodia, 2018).

Akmese uses a dataset from the National Institute of Diabetes and Digestive and Kidney Diseases to classify whether a patient has diabetes. For this purpose, eight variables were selected as input, and the prediction task was performed with various machine learning algorithms. Random Forest achieved 90.1% accuracy, which is better than other methods (Akmese, 2022).

This study, using two different datasets, is aimed to classify the diabetes status and to determine which features are more effective for diagnosis. In addition, the performances of the classification models used were compared, and the effectiveness of each dataset in diagnosis was analyzed. With this approach, the role of data diversity in the early diagnosis of diabetes and the effectiveness of machine learning algorithms are to be revealed.

The remainder of the paper is structured as follows: The technical background is described in Section 2. The experimental results are shown and discussed in the third part, and the study's conclusions are covered in the fourth.

2. Technical Background

In this section, the dataset used in the study, machine learning methods and performance metrics are described.

2.1. Data Set:

The first dataset used in the study, BIT Mesra, was collected by Neha Prerna Tigga and Dr Shruti Garg (Tigganeha, 2019). There are 952 samples in the dataset. The dataset contains 17 independent prediction variables and one binary target or dependent variable (diabetes). The dataset was obtained from Kaggle. The following table shows the variables of the dataset and their value ranges.

The National Institute of Diabetes and Digestive and Kidney Diseases provided the study's second dataset. The purpose of the dataset is to diagnostically predict whether a patient has diabetes using specific diagnostic measures. Several constraints were applied in selecting these samples from a larger database. In particular, all patients here are women of Pima Indian descent who are at least 21 years old. The dataset contains 768 samples and 9 variable types (Pima Indians Diabetes dataset, 2008). The attributes of the dataset and the value ranges of these attributes are given in Table 2.

2.2. Machine Learning Classifiers:

Matlab classification toolbox was used in the study. The classification toolbox contains many algorithms, including classification trees, K-Nearest Neighbours (kNN), class modeling Potential Functions (Kernel Density Estimators), Support Vector Machines (SVM), Random Forest (RF), and Neural Networks. The methods that produce the most successful results on the relevant datasets in the diabetes prediction task are included.

Tabel 1. Attributes and value ranges of BIT Mesra Dataset

Features	**Value Range**
Age	Less than 40, greater than 60
Gender	Male, Female
Family History of Diabetes	Yes, No
High Blood Pressure	Yes, No
Physical Activity	One hour or more, Less than half an hour, More than half an hour, Never
BMI (Body Mass Index)	15-39
Smoking	Yes, No
Alcohol Use	Yes, No
Sleep Duration	4-11
Quality Sleep Duration	4-11
Regular Medication Use	Yes, No
Frequency of Junk Food Consumption	Sometimes, Very Often
Stress Status	Never, Sometimes, Often, Always
Blood Pressure Level	Normal, High, Low
Number of Pregnancies	Numerical Values (e.g. 0 - 3)
Pre-Diabetic Status	Yes, No (0,1)
Urinary Frequency	Not Often, Often

Tabel 2. Attributes and value ranges of the Pima Indian Dataset

Attributes	**Value Range**
Number of Pregnancies	(0-13)
Glucose Level	(85-197)
Blood Pressure Values	(66-110)
Skin Thickness	(23-47)
Insulin Level	(0-846)
BMI(Body Mass Index)	(15-45.4)
Family Diabetes History (Score)	(0.167- 2.288)
Age	(21-59)

2.2.1 Support Vector Machines (SVM)

A potent machine-learning technique for both regression and classification issues is to support vector machines. By establishing a hyperplane for data point classification, SVM seeks to maximize the distance between various classes. The boundary in the data set that offers the largest margin between classes is this hyperplane (Cervantes et al., 2020). Figure 1 illustrates how SVM is used for both linear and non-linear datasets. SVM's regularization features, which enhance overall efficiency, particularly for high-dimensional data sets, are a noteworthy feature of its mathematical foundation, which is founded on optimization approaches. These factors make SVM a popular technique in a variety of domains, including image processing, bioinformatics, and finance.

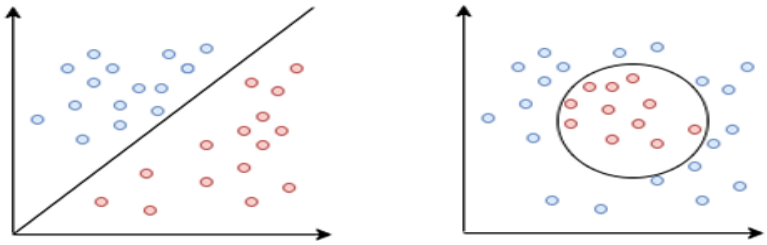

Figure 1. SVM classification notation

2.2.2. Decision Trees

A heuristic and visual machine-learning approach for classification and regression issues is called a decision tree. This technique generates a tree-like structure by branching the data set according to characteristics. By querying a feature at each node, the decision tree separates the dataset into several subgroups. This procedure is repeated until a predetermined stopping condition is met. Typically, leaf nodes lead to a regression or categorization. Their interpretability and explainability make them popular. They may be used in a variety of industries, including marketing, decision support systems, and health, because of their adaptability and simplicity. Nodes and leaves make up decision trees. Figure 2 displays the decision tree's structure. Every internal node in the diagram tests one attribute. The property value is matched by the leaf node. Every leaf node designates a category. (Yildirim et al., 2021).

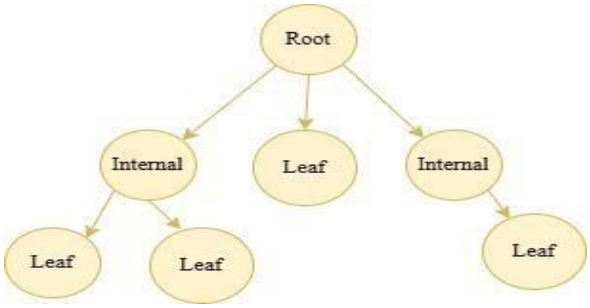

Figure 2. The Structure of Decision Tree

2.2.3. Artificial Neural Network (ANN)

Inspired by the organic nervous system of living things, artificial neural networks are a potent machine learning technique used to solve complicated issues. It is made up of artificial neurons that are coupled to one another. After weighing the incoming data and processing it with the aid of an activation function, each neuron sends the outcome to the layer below. This structure enables it to offer efficient solutions in domains like pattern recognition, regression, categorization by learning patterns, and learning complicated relationships in data (Buscema et al., 2002). The structure of artificial neural networks is illustrated in Figure 3.

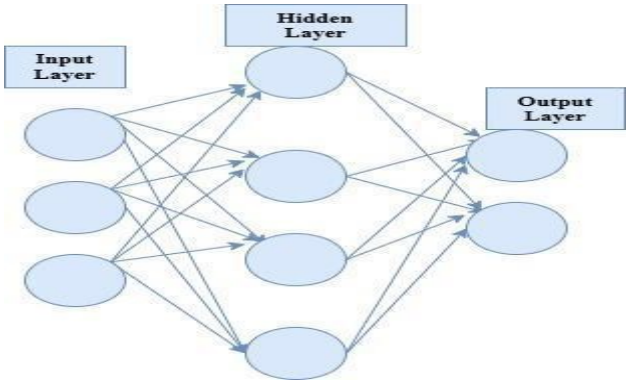

Figure 3. The Structure of ANN

2.2.4. Ensemble Classifiers

To produce a more potent and reliable classifier, ensemble classifiers utilize many machine learning techniques. This method lessens the drawbacks of utilizing a single model, improving generalization performance. Techniques like bagging (bootstrap aggregating), boosting, and stacking are typically used to implement it. While boosting concentrates on minimizing errors by training models sequentially, bagging generates variety by training various data subsets of the same model concurrently. Additionally, ensemble techniques may be optimized for specific situations, such as operating in feature subspaces or resolving data imbalances. To increase accuracy, ensemble classifiers are frequently chosen, particularly for classification and regression tasks (Rahman and Tasnim, 2014).

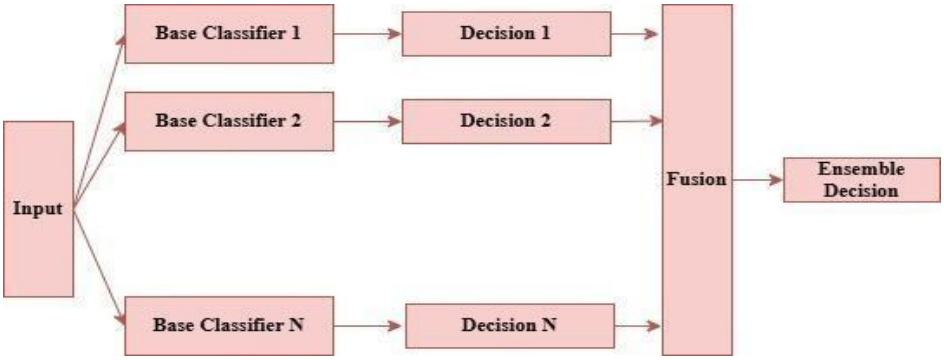

Figure 4. The Structure of Ensemble Classifiers

2.2.5. Algorithms and Parameters

In the experiments with two different diabetes datasets, all classifiers in the Matlab classification toolbox were trained. The algorithms with the highest performance with the BIT mesra dataset and the parameters of these algorithms are given in Table 3.

Table 2. Parameters of the algorithms that give the highest prediction results in the BIT Mesra dataset

No	Algorithm	Parameters
1	Tree (Fine Tree)	{'Maximum number of splits': 100, 'Split criterion': 'Gini's diversity index,' 'Surrogate decision splits': 'Off'}
2	Bilayered Neural Network	{'Number of fully connected layers': 2, 'First layer size': 10, 'Second layer size': 10, 'Activation': 'ReLU', 'Iteration limit': 1000, 'Regulation strength (Lambda)': 0, 'Standardize data': 'Yes'}
3	Fine Gaussian SVM	{'Kernel function': 'Gaussian', 'Kernel scale': 1, 'Box constraint level': 1, 'Multiclass coding': 'One-vs-One', 'Standardize data': 'Yes'}
4	Cubic SVM	{'Kernel function': 'Cubic', 'Kernel scale': 'Automatic', 'Box constraint level': 1, 'Multiclass coding': 'One-vs-One', 'Standardize data': 'Yes'}
5	Narrow Neural Network	{'Number of fully connected layers': 1, 'First layer size': 10, 'Activation': 'ReLU', 'Iteration limit': 1000, 'Regulation strength (Lambda)': 0, 'Standardize data': 'Yes'}
6	Wide Neural Network	{'Number of fully connected layers': 1, 'First layer size': 100, 'Activation': 'ReLU', 'Iteration limit': 1000, 'Regulation strength (Lambda)': 0, 'Standardize data': 'Yes'}
7	Ensemble(Bagged Trees)	{'Ensemble method': 'Bag', 'Learner type': 'Decision tree', 'Maximum number of splits': 951, 'Number of learners': 30, 'Numbers of predictors to sample': 'Select All'}

The algorithms with the highest performance with the PIMA Indian dataset and the parameters of these algorithms are given in Table 3.

Tabel 3. Parameters of the algorithms that give the highest prediction results in the PIMA Indian dataset

No	Algorithm	Parameters
1	Coarse Gaussian SVM	{'Kernel function': 'Gaussian', 'Kernel scale': 11, 'Box constraint level': 1, 'Multiclass coding': 'One-vs-One', 'Standardize data': 'Yes'}
2	Linear SVM	{'Kernel function': 'Linear', 'Kernel scale': 'Automatic', 'Box constraint level': 1, 'Multiclass coding': 'One-vs-One', 'Standardize data': 'Yes'}

3	Medium Gaussian SVM	{'Kernel function': 'Gaussian', 'Kernel scale':2.6, 'Box constraint level': 1, 'Multiclass coding': 'One-vs-One', 'Standardize data': 'Yes'}
4	Quadratic SVM	{'Kernel function': 'Quadratic', 'Kernel scale': 'Automatic', 'Box constraint level': 1, 'Multiclass coding': 'One-vs-One', 'Standardize data': 'Yes'}
5	Boosted Trees(Ensemble)	{'Ensemble Method': 'AdaBoost', 'Learner type': 'Decision tree', 'Maximum number of splits': 20, 'Number of learners': 30, 'Learning rate': 0.1, 'Number of predictors to sample': 'Select All'}
6	Medium Tree(Decision Trees)	{'Maximum number of splits': 20, 'Split criterion': 'Gini's diversity index', 'Surrogate decision splits': 'Off'}
7	Bagged Trees(Ensemble)	{'Ensemble method': 'Bag', 'Learner type': 'Decision tree', 'Maximum number of splits': 767, 'Number of learners': 30, 'Numbers of predictors to sample': 'Select All'}
8	Narrow Neural Network	{'Number of fully connected layers': 1, 'First layer size': 10, 'Activation': 'ReLU', 'Iteration limit': 1000, 'Regulation strength (Lambda)': 0, 'Standardize data': 'Yes'}
9	Cubic SVM	{'Kernel function': 'Cubic', 'Kernel scale': 'Automatic', 'Box constraint level': 1, 'Multiclass coding': 'One-vs-One', 'Standardize data': 'Yes'}

2.3. Evaluation Metrics

The effectiveness of machine learning models is assessed using a variety of performance indicators. A fundamental technique for assessing a model's performance in classification challenges is the confusion matrix. By contrasting the actual labels produced by the model with its anticipated labels, this matrix summarizes four distinct kinds of results: True Negative (FP), False Negative (FN), False Positive (FP), and True Positive (TP) (Patro and Patra, 2014).

True Positive: When a class is accurately predicted by the model to be positive.

False Positive: When the model incorrectly expects a class to be positive.

True Negative: When a class is accurately predicted by the model to be negative.

False Negative: When a class is mistakenly predicted to be negative by the model.

Accuracy, Precision, Recall, F1-Score and Specificity are some of the measurements made using the values in the confusion matrix to achieve reliable accuracy results.

Accuracy: Accuracy value itself. It gives the correct classification rate. It is calculated as in Equation 1.

$$Acc = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (1)$$

The accuracy metric alone is not sufficient to measure the success of the model. Therefore, other metrics must also be calculated.

Precision: It gives the proportion of correctly classified data, i.e. It displays the proportion of projected positive classes that are in fact positive. It is calculated as in Equation 2.

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

Recall (Sensitivity): It gives the proportion of only positive values that are correctly classified. It is calculated as in Equation 3.

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

F1: It is the accuracy and recall values' harmonic mean. Equation 4 is used for calculation.

$$F1 = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (4)$$

Specificity: Expressed as true negative rate (TNR). It gives the ratio of only the data classified as negative to the actual negative data. It is calculated as in Equation 5.

$$Specificity = \frac{TN}{(TN+FP)} \quad (5)$$

3. Experimental Results

The study was carried out with matlab on a computer with 16 GB Ram and Rtx 3050 Ryzen 5600 H. BIT Mesra and Pima Indian datasets were trained and validated with various machine learning classifiers. All experiments were made with 5-cross validations. Experimental results are presented in this section.

3.1 Outcomes of the BIT Mesra Dataset Experiment

The results obtained from the experiments with the BIT Mesra Dataset are given in Table 4.

Table 4. Outcomes of experiments with the BIT Mesra Dataset

Classifier	TP	TN	FP	FN	Acc. (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)
Ensemble(Bagged Trees)	**671**	**244**	**14**	**22**	**96.2**	**0,98**	**0,97**	**0,97**	**0,95**
Wide Neural Network	673	226	12	40	94.5	0,98	0,94	0,96	0,95
Narrow Neural Network	676	223	9	43	94.5	0,99	0,94	0,96	0,96
Cubic SVM	672	224	13	42	94.3	0,98	0,94	0,96	0,94
Fine Gaussian SVM	678	218	7	48	94.2	0,99	0,93	0,96	0,97
Bilayered Neural Network	672	223	13	43	94.1	0,98	0,94	0,96	0,94
Tree(Fine Tree)	656	224	29	42	92.5	0,95	0,94	0,94	0,88

Table 3 compares the performance of different algorithms on the ICT Mesra Dataset. The data in the table are ranked from the highest accuracy value to the lowest accuracy value. SVM (Cubic SVM), Ensemble (Bagged Trees), Decision Tree, Artifical Neural Network algorithms were used in the study. All methods showed the best performances using all features (17/17).

The algorithm that gave the highest accuracy value in this dataset was Bagged trees (ensemble classifiers) with 96.2%. The confusion matrix and ROC curve of the model showing the highest accuracy are as shown in Figure 5. Wide Neural Network and Narrow Neural Network algorithms have obtained results with close accuracy of 94.5%, which shows the suitability of the algorithm for the dataset. Cubic SVM (94.3%) and Fine Gaussian SVM (94.2%) algorithms also have high accuracy rates and give reliable results. On the other hand, the Bilayered Neural Network algorithm showed a slightly lower performance compared to the other methods with an accuracy of 94.1%. The Fine Tree Algorithm achieved a lower accuracy than the other methods with an accuracy of 92.5%, but still showed an acceptable performance. These results reflect the strengths and weaknesses of the algorithms according to the characteristics of the dataset.

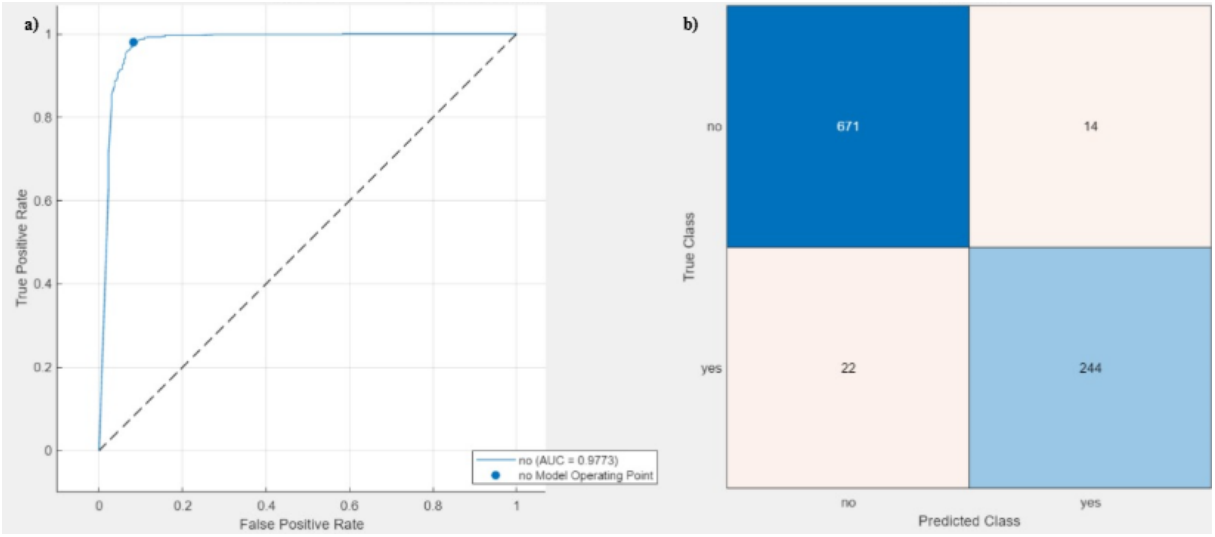

Figure 5. a) ROC Curve and, **b)** Confusion Matrix of Coarse Gaussian SVM Model with BIT Mesra Dataset

In general, the results of the study show that the performance of different algorithms varies according to the characteristics and structure of the data set. The superior performance of the ensemble method reveals that methods that combine the results of more than one model can be more successful especially in complex data sets.

3.3 Outcomes of the Pima Indian Dataset Experiment

The results obtained from the experiments with the Pima Indian Dataset are given in Table 5.

Tabel 5. Results of experiments with the Pima Indian Dataset

Classifier	TP	TN	FP	FN	Acc. (%)	Precision (%)	Recall (%)	F1-Score (%)	Specificity (%)
Coarse Gaussian SVM	**454**	**139**	**46**	**129**	**77.2**	**0,91**	**0,78**	**0,84**	**0,75**
Linear SVM	443	148	57	120	77.0	0,88	0,79	0,83	0,72
Medium Gaussian SVM	440	148	60	120	76.6	0,88	0,78	0,83	0,71
Quadric SVM	442	144	58	124	76.3	0,88	0,78	0,83	0,71
Boosted Trees (Ensemble)	418	164	82	104	75.8	0,84	0,80	0,82	0,66
Medium Tree (Decision Trees)	411	170	89	98	75.7	0,82	0,81	0,81	0,66
Bagged Trees (Ensemble)	415	165	85	103	75.5	0,83	0,80	0,81	0,66
Narrow Neural Network	402	160	98	108	73.2	0,80	0,79	0,79	0,62
Cubic SVM	405	153	95	115	72.7	0,81	0,78	0,79	0,62

The table compares the performance of different algorithms on the Pima Indian Dataset. The data in the table are ranked from the highest accuracy value to the lowest accuracy value. SVM (Cubic SVM), Ensemble (Bagged Trees), Decision Tree, Artifical Neural Network algorithms were used in the study. While all methods were tested, the number of pregnancies variable was removed and all other features were used. The reason for removing the number of pregnancies variable is to minimise the difference due to gender.

Coarse Gaussian SVM model has the best performance with an accuracy of 77.2%. This model minimised the false predictions with 454 true positive (TP) and 139 true negative (TN) predictions from 768 data. The confusion matrix and ROC curve of the model showing the highest accuracy are as shown in Figure 6. The Linear SVM model ranked second with an accuracy rate of 77%, with the Medium Gaussian SVM just below it with 76.6%. There is a small difference between the error rates of these two models, this small difference shows that the performance of the models are close to each other. Boosted Trees (ensemble) performed slightly better than the

other ensemble method, Bagged Trees, with an accuracy of 75.8%, but it was observed that the number of false positives (FP) was relatively higher in the Boosted Trees model. Narrow Neural Network showed a low performance with an accuracy of 73.2%. In addition, the Cubic SVM model showed the lowest performance with an accuracy of 72.7%.

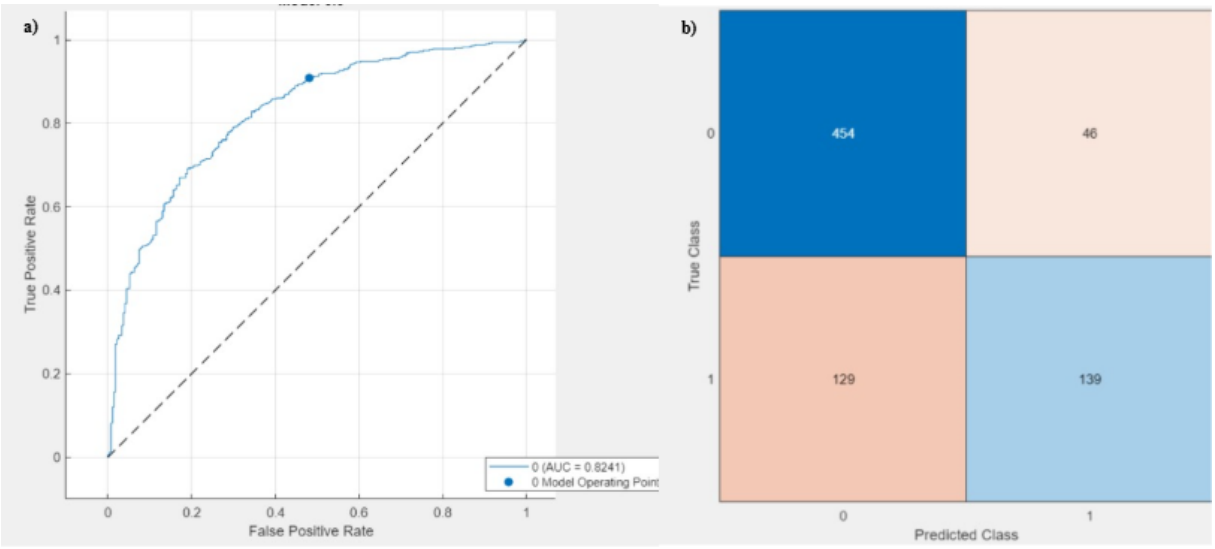

Figure 6. a) ROC Curve and, **b)** Confusion Matrix of Coarse Gaussian SVM Model with Pima Indian Dataset

4. Conclusion

Diabetes mellitus, a chronic metabolic disorder resulting from the inability to stabilise glucose levels in the blood, is caused by inadequate release or ineffective use of the hormone insulin. Although diabetes manifests itself with symptoms such as thirst, polyuria, polydipsia, polydipsia, blurred vision and weight loss, it leads to serious complications such as cardiovascular diseases, nephropathy, neuropathy and diabetic retinopathy in the long term. therefore, early diagnosis of diabetes is important.This study compares and analyzes how well different machine learning classification algorithms perform on two distinct datasets for the early detection of diabetes. In this analysis, the model providing the highest accuracy rate was Coarse Gaussian SVM. It showed a more balanced performance than other models. The error types (FP and FN) and accuracy rates of different models show that each model offers different advantages and disadvantages according to the characteristics of the data set. Comparing the outcomes of the two datasets reveals that the first dataset produces significantly superior results. In the first data set, the Ensemble model performed the best with an accuracy of 96.2%; however, in the second data set, the same model performed worse with an accuracy of 75.5%. Similarly, while Cubic SVM had an accuracy of 94.3% in the first dataset, this rate decreased to 72.7% in the second dataset. The main reason for these differences is the structural differences of the data sets. While the first data set is more balanced or has a clear pattern, the second data set is too complex or noisy. It is also possible that the performance of the algorithms used may vary according to the characteristics of the data sets. Consequently, it is shown that the structure of the data sets has a considerable impact on the performance of various algorithms and sub-models in both data sets. The findings show that the classification performance is significantly impacted by the structural variations of the data sets and the features of the methods. With an accuracy of 96.2%, the Ensemble (Bagged Trees) model produced the best results in the initial data set. This suggests that ensemble approaches function well when dealing with a variety of data.

1. Kaynaklar

Arıkoğlu H, Kaya DE. (2015). Tip 2 diyabetin moleküler genetik temeli; Son gelişmeler. *Genel Tıp Dergisi*, *25*(4), 147-159.

Başer BÖ, Yangın M, Sarıdaş ES. (2021). Makine öğrenmesi teknikleriyle diyabet hastalığının sınıflandırılması. Süleyman Demirel Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 25(1), 112-120.

Buscema M. (2002). A brief overview and introduction to artificial neural networks. Substance use & misuse, 37(8-10), 1093-1148.

Cervantes J, Garcia-Lamont F, Rodríguez-Mazahua L, Lopez A. (2020). A comprehensive survey on support vector machine classification: Applications, challenges, and trends. Neurocomputing, 408, 189-215.

Modak, S. K. S., & Jha, V. K. (2024). Diabetes prediction model using machine learning techniques. Multimedia Tools and Applications, 83(13), 38523-38549.

Önsüz MF, Topuzoğlu A. (2018). İstanbul İlinde Üç Hastanede Ayaktan İzlenen Tip II Diyabetik Hastalarda Glisemik Kontrolün Maliyet Etkinliğinin Değerlendirilmesi. ESTÜDAM Halk Sağlığı Dergisi, 3(2), 1-14.

Patro VM, Patra MR. (2014). Augmenting weighted average with confusion matrix to enhance classification accuracy. Transactions on Machine Learning and Artificial Intelligence, 2(4), 77-91.

Pima Indians Diabetes dataset (May 2008). Pima Indians Diabetes dataset. Available from: http://archive.ics.uci.edu/ml/machine-learning-databases/pima-indians-diabetes/pima-indians-diabetes data. Accessed 15 Dec 2024.

Rahman A. Tasnim S. (2014). Ensemble classifiers and their applications: a review. arXiv preprint arXiv:1404.4088.

Sisodia, D., & Sisodia, D. S. (2018). Prediction of diabetes using classification algorithms. Procedia computer science, 132, 1578-1585.

Tigga, N. P., Garg, S. (2020). Prediction of type 2 diabetes using machine learning classification methods. Procedia Computer Science, 167, 706-716.

Tigganeha N. (2019). Diabetes dataset 2019. https://www.kaggle.com/datasets/tigganeha4/diabetes-dataset-2019. Accessed 15 Dec 2024.

Todkar, SS. (2016). Diabetes mellitus the silent Killer'of mankind: An overview on the eve of upcoming World Health Day!. Journal of Medical & Allied Sciences, 6(1), 39.

Yıldırım M, Çınar A, Cengil E. (2021). Investigation of Cloud Computing Based Big Data on Machine Learning Algorithms. Bitlis Eren Üniversitesi Fen Bilimleri Dergisi, 10(2), 670-682.