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Ensemble stacking classifier model for prediction of diabetes

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ABSTRACT

Diabetes, being a chronic condition, possesses the capacity to instigate a global healthcare catastrophe. This condition can be managed and potentially cured with prompt diagnosis and treatment. Integrating machine learning technology with medical science enables precise prognosis of an individual's susceptibility to diabetes. The proposed work presents the ensemble stacking classifier model. This efficient and effective diabetes prediction model predicts a patient's diabetes risk by combining the output of multiple machine-learning techniques into a single model. The performance parameters of four distinct machine learning classification algorithms K-nearest neighbors (KNN), random forest (RF), support vector machine (SVM), and decision tree (DT) are compared in this study with those of the proposed stacked classifier model. The suggested model is developed using ensemble methods, where the previously discussed algorithms are integrated to create the base classifier layer of the stack classifier. The meta-classifier is implemented in the form of the logistic regression (LR) algorithm. Upon evaluating the performance of both the developed model and its algorithms, it is proved that the proposed model attains a testing accuracy of 88.5%, surpassing the accuracy of all baseline classification algorithms. As a result, this work determines that the ensemble stacking classifier model exhibits higher prediction accuracy than the base classifier algorithms. This finding underscores the model's potential as a viable instrument for predicting diabetes in individuals.

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1. INTRODUCTION

Each year, non-communicable diseases are accountable for nearly 71% of all fatalities globally, or more than 41 million premature deaths [1]. If non-communicable diseases are not treated, it is predicted that they will result in 52 million deaths yearly by 2030 [2]. Diabetes is the most prevalent non-communicable disease, contributing to approximately 46.2% of all fatalities [3], [4]. Type 2 diabetes is a persistent metabolic disorder characterized by elevated blood sugar levels. It is commonly brought on by the body's incapacity to utilize its own produced insulin [5], [6]. Patients diagnosed with diabetes are at an increased risk of mortality due to stroke and other associated causes [7]. However, with consistent surveillance of blood glucose levels, diabetic complications can be effectively prevented or mitigated [8], [9].

According to projections, the number of people living with diabetes in developing countries will reach 228 million by 2030, imposing a significant strain on healthcare systems [10]. A number of recent research investigations have utilized machine learning technology to assist in the detection of diseases, specifically in the precise identification of diabetes using health data from an individual. This strategy aids individuals in implementing preventative measures to manage and surmount this condition in its early stages. An efficacious methodology in the field of machine learning is the approach that amalgamates numerous classification models via stacking, bagging, or boosting techniques. Its accuracy has been shown to be superior to the utilization of solitary algorithms. Previous studies have successfully implemented the ensemble method to assist medical decision-making and predict various diseases. An ensemble stacking classifier-based diabetes prediction model is presented in this paper. This model utilizes particular medical parameters and health measures to forecast the presence of diabetes in an individual. The model is trained using the Pima Indian Diabetes Dataset (PIDD), which assesses its performance using various parameters.

The subsequent content constitutes the paper's outline. Recent work on this subject and the literature review are highlighted in section 2. In addition to describing the methodology utilized in creating and developing the proposed model, section 3 provides theoretical details regarding the algorithms and processes. In section 4, the outcomes and performance of the proposed model are assessed, with a comparison made between the model's parameters and those of the baseline method. In addition to presenting a concluding statement and final evaluation of the research findings, section 5 provides the concluding statement of the study and investigates possible future applications of the designed model.

2. LITERATURE REVIEW

Diabetes is a significant etiological agent in the development of numerous diseases and health conditions. Early detection may enable individuals to implement preventative measures to surmount this condition. Machine learning can produce a predictive model for the early detection of diabetes and other maladies by utilizing individual medical data. Predicting or predisposing to diabetes has been the subject of numerous research studies demonstrating noteworthy outcomes using machine learning models.

Sonar and Malini [11] devised a system that effectively predicted an individual's diabetic risk by combining multiple algorithms. This research made use of support vector machine (SVM), decision tree (DT), and Naive Bayes (NB) algorithms. A robust framework for predicting diabetes is developed by Hasan *et al.* [12]. The framework incorporated various machine learning (ML) techniques, including feature selection, K-fold cross-validation, outlier rejection and filling, missing value filling, and data standardization. Combining these methods improved the accuracy of the predicted weights for calculating the the receiver operating characteristic (ROC) area under curve (AUC) of the ML model. Alanazi and Mezher [13] conducted a study in which they predicted diabetes using a combination of the SVM and random forest (RF) algorithms. The ROC for the proposed model is 99%, and its accuracy rate is 98%. In terms of accuracy, the result indicates that the RF method outperforms the SVM. In their study, Sunge *et al.* [14] employed the C4.5 algorithm and DT models to determine that the model's accuracy is around 72%. Kumar [15] discovered that early diabetes prediction for a patient can be performed precisely using ML's RF method. Babaso *et al.* [16] investigated ML methodologies, including SVM, K-nearest neighbor (KNN), neural networks, NB, and deep learning algorithms in their investigation.

In their study, Kishore *et al.* [17] investigated the metrics of misclassification and accuracy associated with various classification algorithms, including SVM, KNN, DT, RF, and logistic regression (LR). RF exhibits superior performance, boasting an accuracy of approximately 75%. The efficacy of NB and DT classification algorithms is evaluated by Srikanth and Deverapalli [18]. The algorithms achieved approximately 75% and 80% precision measures. An investigation is carried out by Koc and Yeniad [19], employing various classification models, such as SVM, RF, DT, KNN, LR, and gradient boosting. A 77% degree of classification accuracy in Diabetes mellitus is predicted by Jaggi *et al.* [20] utilizing well-known ML algorithms, including RF, KNN, DT, and LR. In contrast to all alternative machine learning approaches evaluated, LR achieved a remarkable accuracy of 78% for the dataset. An ensemble-based multilayer classification algorithm was devised by Fitriyani *et al.* [21], utilizing SVM and DT as base classifiers and LR as the meta-classifier. A substantial improvement in the accuracy of the classification algorithms is observed. The individual classification algorithms exhibit an approximate mean accuracy of 74%, whereas the ensemble-based classification algorithm exhibits an approximately 83% mean accuracy. This demonstrated that ensemble learning is the predominant machine learning method that enhanced the model's predictive performance and precision. An ensemble-based multilayer stacking classification algorithm is implemented by Kalabarige *et al.* [22]. This algorithm comprised two layers of base classifiers and a concluding layer of meta-classifiers. Furthermore, the research demonstrated that algorithmic accuracy is compromised when comparing unbalanced and balanced datasets. The findings indicate that the multilayer stacking classification algorithm achieves an approximate average accuracy of 95%. Bauer and Kohavi [23] empirically contrasted three ensemble learning strategies, including boosting (AdaBoost) and bagging. AdaBoost outperforms the other two methods consistently.

In their seminal work, Jiang *et al.* [24] unveiled SSEM, an innovative method for classification that employs self-adaptive stacking ensembles. The researches [25], [26] examine the efficacy of ensemble learning techniques in the context of machine learning. Based on the J48 and C4.5 classifiers, Kshatri *et al.* [27] proposed a modified ensemble stacking classification algorithm. The accuracy of this recently developed algorithm is superior to that of the normalized ensemble stack classifier. Xu and Wang [28] asserted that the accuracy of the classification algorithms is significantly impacted by data preprocessing. The PIDD set is utilized. The performance capability of a KNN classifier is shown to be enhanced through feature selection and data normalization, as demonstrated by Gupta and Goel [29]. On the F1-scale, the KNN classifier scored 78.10%. It exhibited the following metrics: accuracy of 85.06%, recall of 77.36%, precision of 78.85%, specificity of 89.11%, and error rate of 14.94%.

Zian *et al.* [30] showcased sixteen additional classification algorithms, including LR, NB, and XGBoost, implemented as meta-classifiers within an ensemble-based stacking classification model. The study compared the accuracy variation among models according to the meta-classifier implemented in each model. Additionally, a novel meta-classifier is created, exhibiting enhanced efficacy compared to conventional meta-classifiers. In comparison to other conventional meta-classifiers, the LR meta-classifier produced the most precise outcomes, according to the findings of this study.

3. RESEARCH METHOD

This section provides a detailed explanation of the design and development steps that are used for diabetes prediction. The proposed stacked classifier model is described along with its block diagram. The details of the dataset are also discussed herewith. The parameters for the performance assessment are then thoroughly discussed.

3.1. Dataset characteristics

The PIDD [11] is used in this work. Table 1 shows the health parameters used as the model's input attributes. The dataset contains a sample space of 768 patients. The dataset's target variable is the 9th attribute from Table 1, the 'outcome' variable. This binary class variable displays the result as a 0 or 1, depending on whether the patient is diabetic or non-diabetic. The dataset has no null values. The dataset presents a binary classification problem that can be tackled using classification methodology.

Table 1. Dataset attributes

Sr No.	Attributes
1	Pregnancy
2	Glucose (mg/dL)
3	Blood pressure (mm Hg)
4	Skin thickness (mm)
5	Insulin
6	BMI (body mass index)
7	Diabetes pedigree function
8	Age
9	Outcome (0 or 1)

3.2. Correlation matrix

The correlation between every attribute in the dataset is compared in Figure 1. As shown by the generated plot, there is no strong correlation between any attribute and the objective variable. The sole parameter, denoted as 'glucose', correlates with the 'outcome' variable considered satisfactory. The correlation score between the 'glucose' and the 'outcome' variables is 0.47. Other than that, specific characteristics correlate positively or negatively with the output variable, but the correlation is insignificant.

3.3. Distribution of diabetic patients in the dataset

The dataset is considerably unevenly distributed, as shown in Figure 2. Approximately 500 classes are labeled as 0, representing negative or non-diabetic patients, while 268 classes are labeled as 1, representing positive or diabetic patients. To enhance the accuracy of the ML models, this imbalanced dataset must be transformed into a balanced one [22].

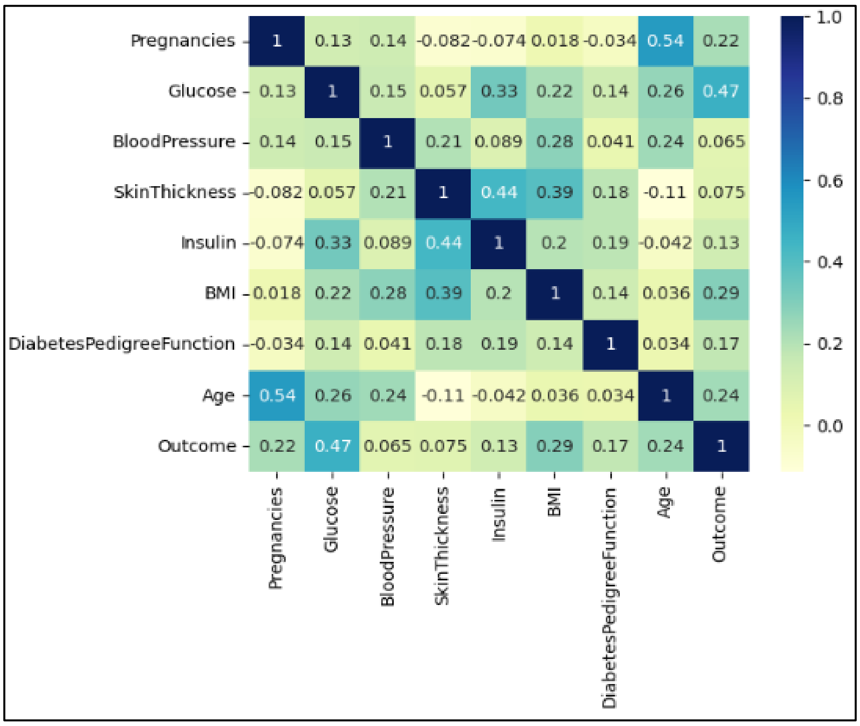

Figure 1. Plot of the correlation matrix for a given dataset

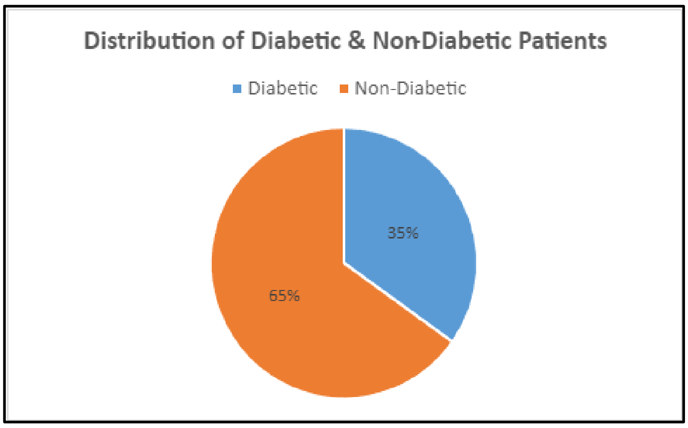

Figure 2. Spread of diabetic patients and non-diabetic patients

3.4. Flowchart

The methodology implemented to develop the ensemble stacking classifier model is illustrated through a flowchart, as shown in Figure 3. Understanding the dataset, gathering a list of all its characteristics, and analyzing their various statistical measures and attributes defined the initial step. The data imbalance depicted in Figure 2 is rectified during the data preprocessing phase to produce a balanced dataset consisting of 500 data points labeled 0 and 500 data points labeled 1 [22]. Data normalization and standardization processes are executed [29], [30]. Following these procedures ensures that every outlier value in the dataset is modified with its corresponding normalized values, thereby preventing any model failures or misclassifications. During this stage, the dataset is split into two portions, with 80% allocated for training and 20% for testing. Following this, the dataset is displayed using statistical charts and graphs, contributing to the ML model's development.

In order to develop the proposed model, a literature review is conducted [11]–[20]. The suitable ML algorithms, including KNN, SVM, DT, and RF, were chosen based on the findings of this study. Furthermore, the ensemble-based stacking classification model [21], [22] is suggested to enhance the accuracy of data prediction and classification. An evaluation is conducted on the performance parameters of each algorithm implemented individually to the dataset. The previously mentioned algorithms are implemented in the stack classifier, which comprises the base classifier layer, and the LR algorithm is the meta classifier [30]. These design stages are then completed for the ensemble stack classification model. Optimal performance for data classification and precise predictions is achieved through iterative modification and enhancement of the designed model. The scores produced by suitable performance parameters are utilized to assess both the ensemble stack classification model and the outcomes of the standard algorithms. Therefore, inferences can be made regarding the accuracy of prediction and classification of the chosen algorithm based on these outcomes.

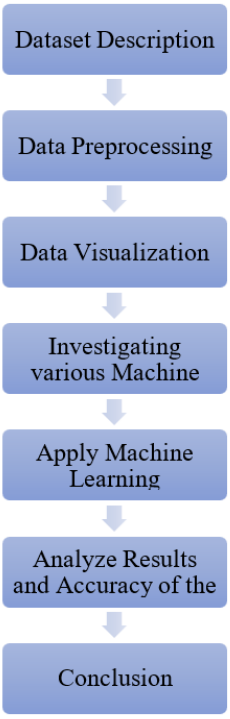

Figure 3. Flowchart

3.5. Machine learning algorithms used

The following section discusses the theory underlying each machine learning algorithm utilized in the design and development of the proposed work. It is necessary to understand the operation and applications of each of these algorithms to conduct an exhaustive analysis. The Sci-kit learn framework, an open-source library for Python, is utilized to implement the programming logic of each of these algorithms. The values of attributes in these functions are modified as necessary to align with the model's specifications.

3.5.1. K-nearest neighbors

The KNN algorithm locates the nearest data points in the training data set, also known as its nearest neighbors, to predict a new data point [10]. This distance is computed using metrics like Euclidean, Manhattan, or Minkowski distances. Based on the results from the distance metrics, the closest neighbors are designated by the constant positive integer K. The class set is used to select K's value. Thus, a higher value of K would be suitable for a dataset with more outliers or noise.

3.5.2. Support vector machine

A hyperplane is created using SVM, categorizing the data points into multiple groups. It can produce a single hyperplane or a string of hyperplanes in high-dimensional space. Regression and classification both employ these hyperplanes. SVM can categorize the entities and separate them into designated classes.

3.5.3. Decision tree

This algorithm is used when the output variable has a definite nature [16]. A model with a tree-like structure involved in the classification process based on input features is called a decision tree. Any input variable type may be used, including continuous, discrete, and graph variables.

3.5.4. Stacked classifier model

The ensemble stack classification model can be seen as a block diagram in Figure 4. The first layer involves a stack classifier built using KNN, SVM, DT, and RF as the base classifiers. The input data is fed to each method individually. The combined output of each base classifier is then fed to a meta-classifier, which integrates the predictions of multiple base classifiers. Here, the RF, DT, KNN, and SVM outputs from the base classifiers are used as input to the meta-classifier, which is the LR classifier. To produce the best overall prediction, the meta-classifier must learn how to balance the predictions of each of the individual base classifiers.

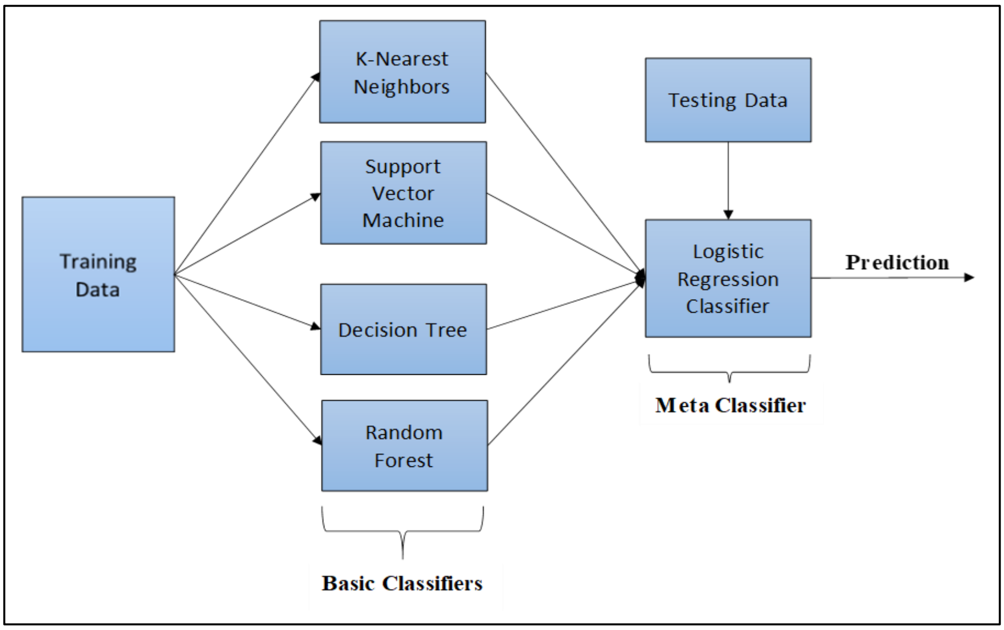

Figure 4. Block diagram of the stacked classifier model

3.6. Performance parameters used for evaluating the algorithms

Multiple performance parameters are employed to assess and compare the ML algorithms' outcomes. The output score of each parameter for the respective algorithm is analyzed, and the results and conclusions are drawn from these values. Parameters like accuracy, recall, F1-score, and Matthew's correlation coefficient (MCC) are used to analyze the performance of individual algorithms using the stacked classifier model.

4. RESULTS AND DISCUSSION

A comparison table is developed to evaluate the performance of both the training and testing datasets. This table includes the classification performance of each algorithm. Additionally, bar plots are generated to showcase the comparison of output values of each algorithm concerning different performance parameters.

4.1. Training performance of all algorithms

The results of the classification problems for each algorithm are presented in Table 2. The stacked classifier model exhibits the highest accuracy regarding performance parameter scores, followed by the RF algorithm. Concerns are expressed, however, regarding the possibility of overfitting.

4.2. Testing performance of all algorithms

The efficacy of each algorithm, measured by the provided performance parameters, is detailed in Table 3. This assessment examines the algorithms' predictive capability. With the most significant average performance score among all algorithms, the stacked classifier model receives the highest possible score in every performance parameter. The findings of this study mitigate the assertions of overfitting and demonstrate the robustness of the model.

Table 2. Evaluation of training performance of all algorithms

Training data	Accuracy	MCC	F1-score	Recall	Average (%)
KNN	85.5%	73.45%	86.33%	92.88%	84.54%
SVM	100%	100%	100%	100%	100%
DT	81.5%	69.74%	85%	90.08%	81.58%
RF	99.125%	98.5%	99.25%	99.24%	99.02%
Stacked classifier	100%	100%	100%	100%	100%

Table 3. Evaluation of testing performance of all algorithms

Testing data	Accuracy	MCC	F1-score	Recall	Average (%)
KNN	71.5%	44.61%	72.25%	80.37%	67.18%
SVM	87%	66.17%	79.3%	62.62%	73.77%
DT	71.5%	55.7%	77.93%	82.24%	71.84%
RF	84.5%	70%	84.91%	84.11%	80.88%
Stacked classifier	88.5%	70.52%	85.5%	79.44%	80.99%

4.3. Comparison of training performance of all algorithms

Figure 5 presents a comprehensive comparison of the training performance of all algorithms for each evaluation parameter. The stacked classifier model performs similarly to the baseline algorithms during training. The aforementioned indicates that the stacked classifier model is learning at a similar rate as the other models, correctly identifying the appropriate class (recall), producing a significant number of accurate predictions (accuracy), and demonstrating strong performance on binary classifications MCC.

However, it is also important to note that it incorrectly classifies a similar number of cases (F1) as the other models during training. The stacked classifier model's comparable training performance raises concerns about the potential for overfitting. This observation underscores the importance of model validation and the need for further investigation into optimizing the stacked classifier model's learning efficiency.

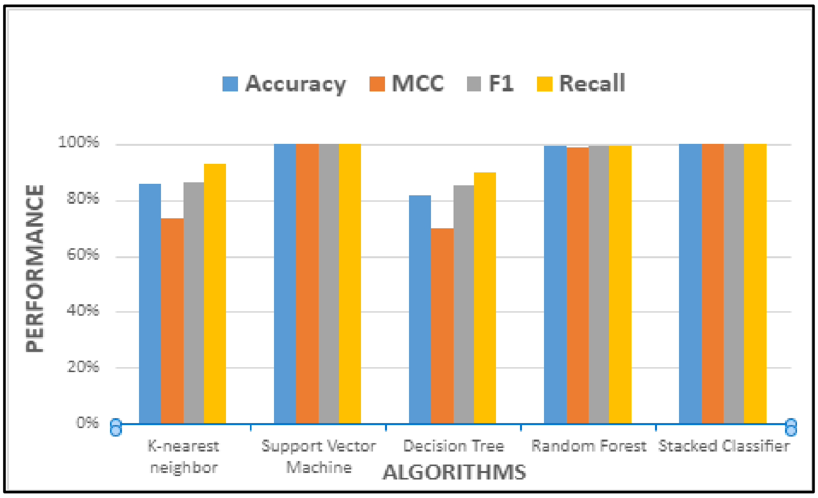

Figure 5. Comparison plot of training performance of all algorithms

4.4. Comparison of testing performance of all algorithms

A comprehensive comparison of the efficacy of all algorithms for each evaluation parameter is presented in Figure 6. The stacked classifier model consistently exhibited superior performance in every performance metric compared to the baseline algorithms. This indicates that the stacked classifier model exhibits strong performance on binary classifications MCC, correctly identifies the appropriate class (recall), and produces a significant number of accurate predictions (accuracy). Furthermore, it incorrectly classifies fewer cases (F1), attesting to its robustness. Importantly, the consistent performance of the stacked classifier model in both the training and testing phases effectively addresses any concerns regarding overfitting. This consistency ensures that the model is not merely memorizing the training data but can generalize to unseen data, thereby providing reliable and robust predictions.

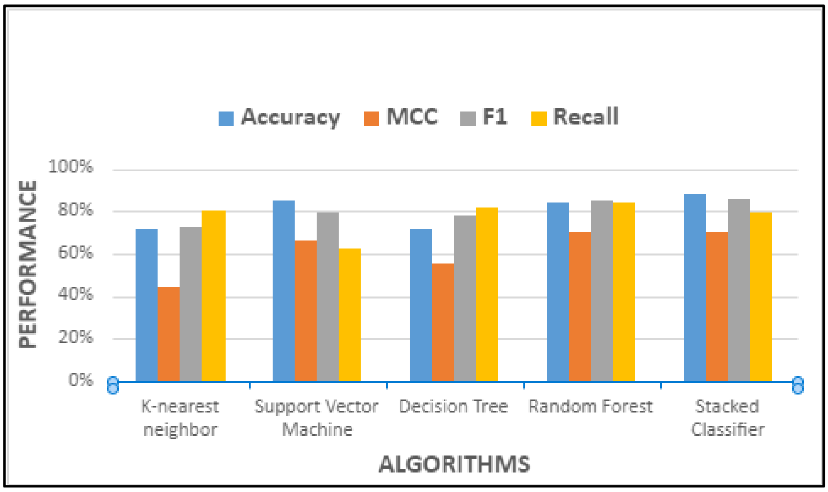

Figure 6. Comparison plot of testing performance of all algorithms

5. CONCLUSION AND FUTURE SCOPE

This work evaluated how machine learning algorithms can predict diabetes and attempted to develop a model that can predict diabetes in a patient with accuracy and precision. The developed stacked classifier model, a mix of methods such as SVM, DT, KNN, and RF using ensemble methodology, shows promising results. For the testing data, i.e., for diabetes prediction, the ensemble stacking classifier model showed the highest accuracy of 88.5%, followed closely by the SVM at 87%. The overall average performance of all the evaluation parameters for the developed stacked classifier model is also better than the individual algorithm's average score. The average testing performance parameter score is about 81%, which signifies that the model makes better predictions, better classifications, and substantially better coverage of the dataset than all other baseline classification algorithms. The KNN and DT algorithms both showed the lowest accuracies of 71.5%.

These findings imply that the prediction accuracy of individual classifier algorithms is enhanced when combined, as shown in the ensemble stacking classifier model. This indicates that machine learning algorithms can be used as practical tools for forecasting diabetes and help in the timely diagnosis and prediction of diabetes in a patient.

Machine learning algorithms can analyze vast datasets and uncover patterns humans might overlook. These models can become more accurate and valuable if medical records and other health data are decentralized. Another promising area for research is using the data collected from wearable technologies or sensors in diabetes prediction models for real-time detection. Machine learning algorithms can deliver more accurate and fast predictions of diabetic risk by gathering real-time data on parameters such as blood glucose levels, physical activity, and sleep habits.

Furthermore, diabetes prediction models have the potential to be integrated into clinical decision-making procedures. These models can assist, guide, and enhance the treatment regimens to prevent or manage diabetes by providing healthcare providers with precise and tailored estimates of diabetic risk in a patient. Overall, the findings from this study have significant future scope and present an opportunity for healthcare practitioners attempting to enhance the accuracy of diabetes diagnosis and prognosis.

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