Title Page:

Innovative AI-driven Glaucoma Screening with Comparative study of Support Vector Machine and Decision Tree Algorithms for the Analysis of Retinal Fundus Images.

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Keywords:Support Vector Machine algorithm,Decision Tree algorithm , eye treatment, glaucoma, detection.

ABSTRACT

Aim: This study evaluates the glaucoma detection accuracy using Decision Tree (DT) and Support Vector Machine (SVM) machine learning approaches. **Materials and Methods:** The glaucoma detection dataset, on which the SVM is used, consists of 145461 records. This work compares the machine learning methods SVM and DT and proposes and creates a standard module for glaucoma detection. For evaluation, 1010 sample records were gathered from each group. The sample records were measured using clinical analysis; the evaluation's enrollment ratio is 1, its confidence percentage is 95%, its pretest power percentage is 80%, and its alpha and beta values are 0.05 and 0.5, respectively. For accuracy, the obtained significance value (p), which is less than 0.05, is 0.001. The ultimate accuracy of both procedures was calculated and published. **Results:** On the utilized dataset, the SVM classifier machine learning algorithm predicts glaucoma detection with 96.00% accuracy, whereas the decision tree classifier predicts the same event with 84.00% accuracy.**Conclusion:** The Support Vector Machine (SVM) algorithm outperforms the decision tree method in terms of glaucoma detection prediction, according to the study.

Keywords:Support Vector Machine, algorithm,Decision Tree, eye treatment, glaucoma, detection.

INTRODUCTION:

One of the most common causes of blindness, glaucoma can cause very gradual, mild vision loss. Retinal fundus imaging can be used to screen for glaucoma noninvasively, and early detection is critical to preserving vision. Artificial intelligence (AI) has evolved into powerful medical image analysis that could revolutionize the way glaucoma is diagnosed.

This work explores the creation of a new AI-powered glaucoma screening method using retinal fundus images. We investigate how well two machine learning algorithms—a decision tree and a support vector machine (SVM)—perform in evaluating these images. To determine the best method for this application, we evaluated how well it discriminates between eyes with and without glaucoma.

Glaucoma detection has 105 scientific articles published in IEEE Xplore, 165 scientific articles in Google Scholar and 34 articles identified in ScienceDirect. Since the best representation of glaucoma detection is sometimes difficult to achieve, Bayesian methodology provides an additional way to incorporate prior data into detection models. to predict a situation where foreknowledge is either unreliable or useless. As a result, everything seems to be stable. This study investigates how artificial intelligence can help diagnose glaucoma by comparing two machine learning techniques, decision tree (DT) and support vector machine (SVM). By looking at images of the retinal fundus, we try to evaluate how well these algorithms distinguish between healthy and glaucomatous eyes.The analysis revealed a gap in the research: although several approaches have been proposed to detect glaucoma, most of these methods. has low accuracy. Many studies have shown that the decision tree (DT) performs poorly and provides low accuracy in glaucoma detection. Analyzing and comparing them is the best way to find out which classification algorithm is the most accurate. Therefore, this research compares the accuracy and precision of the Decision Tree (DT) algorithm and the Support Vector Machine (SVM) algorithms.

MATERIALS AND METHODS:

The data analytics lab at Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, where this study was conducted, has incredibly well-configured technologies that aid in producing reliable results. There were two groups in total that were taken into consideration for the research: group 1 had ten sample sizes, and group 2 also had ten sample sizes. G-power 0.95, alpha value 0.005, beta value 0.95, and confidence interval 95% are used in the computation. Kerneler (2019) obtained the dataset for the study from the Kaggle website.

Pseudocode for Support Vector Machine(SVM) Algorithm:

Step 1: Preparing the data

1.1 Load the collection of fundus pictures 1.2 Prepare the photos (resize, normalize, sharpen contrast, etc.)

1.3 Take relevant features (such as texture, optic disc, and cup-to-disc ratio) and extract them from photos.

Step 2: Divide Information

2.1 Separate the dataset into testing and training sets (for example, 30% testing and 70% training).

Step 3: SVM Model Training

3.1 Initialize the SVM model using the preferred kernel (radial, polynomial, or linear basis function, for example).

3.2 Use the training dataset to train the SVM model.

3.2.1 Feed the SVM with the retrieved features and the associated labels (glaucoma positive or negative).

3.2.2 If necessary, use cross-validation to modify model parameters (such as kernel parameters and regularization parameter C).

Step 4: Model Evaluation

4.1 Predict labels for the test dataset using the trained SVM model

4.2 Evaluate the model performance using appropriate metrics (e.g., accuracy, precision, recall, F1-score)

4.3 Visualize the results (e.g., confusion matrix, ROC curve)

Step 5: Fine-tuning (optional)

5.1 If performance is not satisfactory, fine-tune the model by adjusting parameters or exploring different kernels

5.2 Re-train and evaluate the model iteratively until desired performance is achieved

Step 6: Deployment (optional)

6.1 Once satisfied with the model's performance, deploy it for glaucoma detection in real-world scenarios

6.2 Implement necessary integration with existing healthcare systems if applicable

Support vector machine:

The sklearn.linear_model library of the SVM class was used for the data training in this investigation. Read Glaucoma Detection.csv by opening the file. Eighty percent of the dataset is utilized for training, and the remaining twenty percent is used for testing. The dataset's data records are distributed randomly. Three of the 10 SVM classifiers are created using the training dataset after the output variable has been defined. The testing dataset is estimated using the training dataset. Accuracy is obtained after the SVM classification design is tested.

Pseudocode for Decision Tree (DT) Algorithm:

Step 1: Begin by using the complete dataset.

- When creating the decision tree, the complete dataset is taken into account at first.

Step 2: Decide which attribute is best to split on

- Examine every feature in the dataset and choose the one that yields the optimal split. Usually, to do this, a metric like entropy, Gini impurity, or information gain is calculated.

Step 3: Divide the dataset according to the chosen characteristic

- Create subgroups inside the dataset according to the chosen attribute's values.

Step 4: For every subset, repeat recursively

- Repeat steps 2 and 3 recursively for each subgroup that the split creates until one of the halting criteria is satisfied.

Step 5: Specify when to stop.

- Decide when to stop dividing even more. This may be predicated on requirements like: - Every instance in a subset is a member of the same class.

- The tree reaches its maximum depth.

- A node reaches a minimum number of instances.

Step 6: Establish leaf nodes.

- Construct a decision tree leaf node with the majority class label for the subset when a stopping requirement is satisfied.

Step 7: Construct the decision-tree.

- Create the decision tree by connecting parent nodes to corresponding child nodes when the recursion unwinds.

Step 8: Prognosticate with the decision tree

After the decision tree is built, follow the split decisions based on attribute values to traverse the tree from the root node down to the leaf nodes in order to anticipate future instances.

Decision Tree(DT):

The Decision Tree (DT) class from the sklearn ensemble package was used to train the data used in this investigation. Eighty percent of the dataset is utilized for training, and the remaining twenty percent is used for testing. The dataset's data records are distributed randomly. Random samples are chosen from the dataset, and decision trees are put together to predict the outcome. Every scenario was placed to a vote, and the person who received the most votes was declared the winner. The Decision Tree (DT) algorithm is used.

This study was implemented using Google collab and SPSS software, and hardware specifications needed in a system for evaluation is an intel i3 processor, 50GB Hard Disk Drive, 4GB and Random Access Memory (RAM) and software specifications needed is a windows operating system.

STATISTICAL ANALYSIS

The SPSS tool is used to statistically assess the work in addition to experimental analysis. The mean, standard deviation, accuracy, and standard error mean were the research objectives. The SVM and DT algorithms were compared using an independent sample T-Test.

RESULTS

Table 1:shows the accuracy findings derived from contrasting the Support Vector Machine (SVM) and Decision Tree (DT) for analysis with various iterations.

Table 2: This table displays the various parameters for each of the two groups. The accuracy, recall, F1 Score, and support for SVM and DT have been calculated. A comparison between the two groups shows that SVM performs better in terms of accuracy (96.00%) than Decision Tree (DT).

The statistical analysis of Decision Trees (DT) and Support Vector Machines (SVM) using various test datasets is displayed in Table 3.

Table 3:The table shows that when compared to Decision Trees (DT), Support Vector Machines (SVM) yield higher accuracy.

Table 4:The statistical analysis of the Significant values for both groups is shown in Table 4. The accuracy between the two groups differs by a very little amount (0.001). That is why Decision Tree (DT) is inferior than Support Vector Machine (SVM).

Figure 1:The mean accuracy of Decision Tree (DT) and Support Vector Machine (SVM) was deduced in Figure 1. The outcomes demonstrated that the SVM's accuracy (96.00%) is higher than the DT's accuracy.

DISCUSSION:

Two groups of people experimented with Decision Trees (DT) and Support Vector Machines (SVM) by varying the test size. As per the SPSS testing data (Figure 1), the accuracy of SVM is 96.00%, whereas the accuracy of DT is 84%. This demonstrates why Support Vector Machine (SVM) outperforms Decision Tree (DT). The developed SVM algorithmic classification model performed better than the DT in terms of comparison accuracy (96.00%), according to the SPSS.

Despite the good results that the provided technique achieved, there are still several limitations to the study. The findings obtained by assessing accuracy on huge datasets may not be sufficient. Furthermore, it is undesirable that the mean error in SVM is higher than in DT.

final result. Reducing the mean error considerably improves the current study effort. One possible way to increase accuracy and reduce mean error in the algorithms is to apply optimization algorithmic approaches to them. There is also the option of applying feature selection techniques before dataset classification to improve classifier accuracy and get desired outcomes.

CONCLUSION:

Using decision trees, a machine learning classifier known as Support Vector Machine (SVM) increases accuracy. The research study shows that the Support Vector Machine (SVM) method appears to have a higher accuracy in glaucoma identification than Decision Tree (DT). It has been demonstrated that SVM significantly outperforms DT in the detection of glaucoma. The Support Vector Machine (SVM) technique produces higher accuracy (96.00%) than the Decision Tree (DT) approach (84.00%), according to the study's findings.

DECLARATION:

Conflicts of Interests:

No conflicts of interest in this manuscript.

Author Contributions:

Author Y. Yamini Reddy played a key role in collecting and analysing data as well as writing the manuscript. Additionally, Y. Yamini Reddy contributed significantly to conceptualization, data validation and providing critical feedback during manuscript reviews.

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TABLES AND FIGURES

Table 1: Accuracy values of SVM and DT algorithms obtained for each iteration while evaluating the dataset for various test sizes.

GROUP	ACCURACY
SVM	96
SVM	95
SVM	99
SVM	94
SVM	95
SVM	98
SVM	99
SVM	96
SVM	97
SVM	99
DT	84
DT	83
DT	80
DT	82
DT	81
DT	79
DT	83
DT	78
DT	82
DT	80

GROUP STATISTICS

	GROUP	N	Mean	Std. Deviation	Std. Error Mean
ACCURACY	SVM	20	96.3500	1.66307	.37187
	DT	20	81.1500	2.36810	.52952

Table 2: Group Statistics Results-SVM and DECISION TREEalgorithm

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
ACCURACY	Equal variances assumed	1.571	.218	23.491	38	.000	15.20000	.64706	13.89010	16.50990
	Equal variances not assumed			23.491	34.075	.000	15.20000	.64706	13.88513	16.51487

Table 3:Independent sample test for significance and standard error determination. P-value is less than 0.00 considered to be statistically significant and 95% confidence intervals were calculated.

GGraph

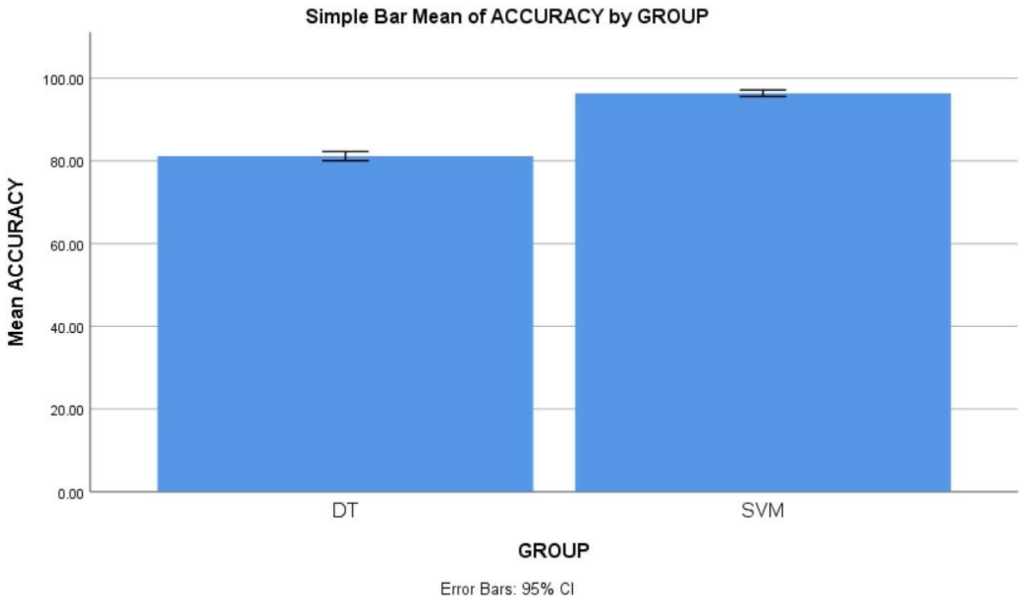

Fig.1. These results underscore SVM superior predictive performance and its potential to enhance traffic evaluation.This comparison is graphically represented with the X-axis denoting "SVM vs DT algorithm," while the Y-axis represents "Mean Accuracy."The Error bar is represented by ± 2.

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