Title Page:

Transformative Approaches in Ophthalmology with performance Assessment of Support vector machine algorithm against Random forest Algorithm in Glaucoma Detection from retinal images.

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Keywords:Support Vector Machine , Random forest algorithm , eye treatment, glaucoma, detection.

ABSTRACT

Aim: In this article, the Random Forest algorithm (RF) and Support Vector Machine (SVM) machine learning approaches are used to evaluate the accuracy of glaucoma detection.**Materials and Methods:** There are 145461 entries in the glaucoma detection dataset, which is utilized to train the SVM. This work suggests and develops a standard module for glaucoma detection and compares the machine learning techniques of SVM and RF. Ten thousand sample records were taken from each group for assessment. Clinical analysis was used to measure the sample records; the evaluation's alpha and beta values are 0.5 and 0.05, respectively, and its enrollment ratio is 1. Its confidence percentage is 95%, its pretest power percentage is 80%, and its pretest power percentage is 80%. The obtained significance value (p) for accuracy is 0.001, which is less than 0.05. Both techniques' final accuracy was determined and released. **Results:**SVM classifier machine learning algorithm predicts glaucoma detection with 98.00% accuracy on the used dataset, while random forest method classifier predicts the same event with 96.00% accuracy**.Conclusion:** The Support Vector Machine (SVM) algorithm demonstrates superior performance in glaucoma detection prediction when compared to the random forest technique, according to the study.

Keywords:Support Vector Machine , Random forest algorithm , eye treatment, glaucoma, detection.

INTRODUCTION:

Glaucoma is a prevalent cause of blindness that might result in modest visual loss that happens very gradually. Early identification of glaucoma is crucial to maintaining vision and can be achieved with noninvasive retinal fundus imaging screening. The development of artificial intelligence (AI) into potent medical image analysis has the potential to completely change the way glaucoma is diagnosed.

The development of a novel AI-powered glaucoma screening technique employing retinal fundus photos is investigated in this paper. We examine the performance of two machine learning techniques in analyzing these images: a support vector machine (SVM) and a decision tree. We assessed the method's ability to distinguish between eyes with and without glaucoma in order to determine which is optimal for this application.

There are 34 publications found in ScienceDirect, 165 scientific articles in Google Scholar, and 105 scientific articles published in IEEE Xplore about the detection of glaucoma. Bayesian approach offers an additional means of incorporating previous data into detection models, since it might be challenging to produce the optimum depiction of glaucoma detection in certain cases. to forecast an event in which knowledge is either worthless or untrustworthy. Everything appears to be stable as a result..Support vector machines (SVM) and random forests algorithm (RF) are two machine learning techniques that are compared in this study in order to gain a better understanding of how artificial intelligence might help identify glaucoma. We assess the ability of these algorithms to discriminate between healthy and glaucomatous eyes using pictures of the retinal fundus.A research gap was identified by the analysis: while glaucoma can be detected using a variety of techniques, the majority of these procedures have low accuracy. Numerous research have demonstrated that the Random Forest algorithm (RF) has poor performance and low accuracy when it comes to glaucoma identification. The best method to determine which classification algorithm is the most accurate is to analyze and compare them. Thus, this study compares the precision and accuracy of the Random Forest (RF) and Support Vector Machine (SVM) approaches.

MATERIALS AND METHODS:

The remarkably well-configured technologies in the data analytics lab at Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, where this study was done, help to produce results that can be trusted. In total, two groups were considered for the study: group 1 had 10 sample sizes, and group 2 had ten sample sizes as well. The computation uses G-power 0.95, alpha value 0.005, beta value 0.95, and confidence interval 95%. The dataset used in the study was downloaded from the Kaggle website by Kerneler (2019).

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 Utilizing the proper metrics (such as accuracy,precision,recall,F1-score)

4.3 Visualize the results(such as 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. Of the dataset, twenty percent is used for testing and the remaining eighty percent is used for training. 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 Random Forest (RF) Algorithm:

Naturally, the Random Forest algorithm may be found here, divided into six steps:

Step 1: Initialize factors

Establish the number of trees, maximum depth, and maximum features, among other factors.

Step 2: Bootstrap Sampling

To generate bootstrap samples for each tree, choose samples at random from the dataset using replacement.

Step 3: Feature Subset Selection

Choose a subset of characteristics at random for each tree to take into account for determining the optimal split.

Step 4: Create Decision Trees

With every tree:

- Using the bootstrap sample and the chosen features, determine the optimal split.

- Make nodes, then divide the data recursively until the end conditions are satisfied.

Step 5: Aggregate Predictions

By combining predictions from all trees, determine the class for every new instance.

Step 6: Last-Minute Forecast:

Select the majority class from the combined forecasts to determine the final prediction.

The process of building a Random Forest ensemble and applying it to classification tasks is described in these phases.

Random Forest(RF):

The sklearn ensemble package's Random Forest (RF) class was utilized to train the data used in this study. Of the dataset, twenty percent is used for testing and the remaining eighty percent is used for training. The data records in the dataset are dispersed at random. To anticipate the result, decision trees are created using randomly selected samples from the dataset. Each scenario was put to a vote, and the winner was determined by tallying the votes cast. It makes use of the Random Forest (RF) algorithm.

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 RF 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 Random Forest (RF) 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 RF have been calculated. A comparison between the two groups shows that SVM performs better in terms of accuracy (98.00%) than Random Forest (RF).

The statistical analysis of Random Forest (RF) and Support Vector Machines (SVM) using various test datasets is displayed in Table 3.

Table 3:The table shows that when compared to Random Forest (RF), 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 Random Forest (RF) is inferior than Support Vector Machine (SVM).

Figure 1:The mean accuracy of Random Forest (RF) and Support Vector Machine (SVM) was deduced in Figure 1. The outcomes demonstrated that the SVM's accuracy (98.00%) is higher than the RF's accuracy.

DISCUSSION:

Two sets of people varied the test size in an experiment involving Random Forest (RF) and Support Vector Machines (SVM). Figure 1 from the SPSS testing data shows that the accuracy of RF is 96% and the accuracy of SVM is 98.00%. This illustrates the superior performance of Support Vector Machine (SVM) over Random Forest (RF). The SPSS indicates that in terms of comparison accuracy (98.00%), the proposed SVM algorithmic classification model outperformed the RF.

The study still has a number of limitations even with the positive outcomes that the given technique produced. The results of evaluating accuracy on large datasets might not be enough. The mean error in SVM being higher than in RF is also desired.

final result. Improving the mean error significantly enhances the current research endeavor. Optimizing the algorithms through algorithmic ways to reduce mean error and boost accuracy is one potential solution. Feature selection approaches can also be used in advance of dataset classification to increase classifier accuracy and achieve desired results.

CONCLUSION:

Accuracy is increased using the Support Vector Machine (SVM), a machine learning classifier that uses decision trees. Random Forest (RF) is not as accurate in identifying glaucoma as Support Vector Machine (SVM) approach, according to the research study. SVM is proven to perform much better than RF in the identification of glaucoma. The study found that the Random Forest (RF) approach yields lower accuracy (96.00%) than the Support Vector Machine (SVM) strategy (98.00%).

DECLARATION:

Conflicts of Interests:

No conflicts of interest in this manuscript.

Author Contributions:

Author Y. Yamini Reddy played a key role in collecting and analyzing 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 RF algorithms obtained for each iteration while evaluating the dataset for various test sizes.

GROUP	ACCURACY
SVM	98

SVM	99
SVM	97
SVM	96
SVM	97
SVM	96
SVM	99
SVM	98
SVM	99
SVM	96
RF	96
RF	91
RF	89
RF	91

RF	89
RF	90
RF	90
RF	92
RF	93
RF	91

GROUP STATISTICS

	GROUP	N	Mean	Std. Deviation	Std. Error Mean
ACCURACY	SVM	20	97.1500	1.53125	.34240
	RF	20	91.5000	2.43872	.54531

Table 2: Group Statistics Results-SVM and RANDOM FOREST algorithm

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	1.390	.246	8.775	38	.000	5.65000	.64390	4.34650	6.95350
	Equal variances not assumed			8.775	31.966	.000	5.65000	.64390	4.33837	6.96163

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.

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 RF algorithm," while the Y-axis represents "Mean Accuracy."The Error bar is represented by ± 2.