



Classification of The Cause of Eye Impairment Using Different Kinds of Machine Learning Algorithms

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ABSTRACT

This study aims to create a machine learning-based method for categorizing ocular impairment. Congenital, refractive error, age, diabetes, and unknown are the five primary causes that specialists consider. The suggested technique automatically classifies patients into one of the five groups based on their unique features by evaluating the ODIR dataset of patient records, which includes numerous demographic and clinical information, and utilizing machine learning algorithms. Most previous studies in this area have focused on classifying illnesses; hence, this study's main contribution is its innovative focus on categorizing the causes of eye disorders.

To the best of our knowledge, no ocular dataset has a label that specifies the cause of eye disease. The classes of eye disease have been added by Ophthalmologists.

Better patient outcomes and more effective use of healthcare resources can be achieved by increasing the precision of physicians' diagnoses and streamlining their decision-making. Compared to the other classification methods, the Quadratic SVM model has the highest accuracy of 71.3%.

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Keywords: Eye Impairment, Congenital, Refractive Error, Ageing, Diabetes, Machine Learning, Clinical Variables.

1. Introduction

Ocular disease is a devastating condition that can drastically alter a person's standard of living. For instance, it has been reported globally that at least 2.2 billion people worldwide have a near or far vision impairment. Vision impairment might have been avoided or is still being addressed in at least one billion of these cases. Due to the complexity of the human eye and the great variety of eye disorders^[9,10], early identification of eye diseases is crucial to provide prompt and efficient treatment. The deep learning for eye disease categorization model employs machine learning strategies to assess and foresee eye disorders. Using deep neural networks that have already been trained, this method may identify patterns and characteristics in massive data sets^[12]. Next, particular eye illnesses were included as predictors by refining the model with smaller data sets. Pre-trained models may make accurate predictions on new, smaller datasets by using what they

have learned in the past. They can assess the risk for disease, provide timely diagnoses, and propose effective treatments^[2]. For instance, Kaggle provides publicly available datasets relevant to eye illness to alter the data and apply models. Identifying and categorizing visual impairments early is crucial to prevent more severe complications. People who develop vision difficulties later in life often have a complete or near-complete loss of sight^[7, 9]. As most researchers have discovered, however, identifying and categorizing Visual diseases is difficult because of the limited number of datasets available. Therefore, many Ophthalmologists competent in medicine have attempted to categorize and evaluate many forms of eye illness. For instance, most have concluded that retinal problems are the leading cause of blindness, making early identification crucial^[7]. Researchers have shown that utilizing neural networks to detect and categorize illnesses helps diagnose and treat eye problems^[1, 8].

Our study focuses on visual impairment by properly classifying eye syndromes using numerous machine learning models. The processes in this study are divided into three stages. The first stage is retrieving the ocular illness dataset and, in cooperation

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with an eye professor, determining the root causes of each sickness. The doctor has found the underlying causes of glaucoma, idiopathy, age-related diabetes, hypertension, refractive error, congenital trauma, inflammation, venous blockage, and optic atrophy. Following identifying the underlying causes of eye problems, numerous machine-learning models and processes were applied to the data. For instance, one of the processes used is a feature selection technique. The third stage included selecting the most relevant feature for each rationale. By using deep learning to train neural networks on enormous datasets of optic nerve pictures, clinicians can more accurately diagnose and treat glaucoma. By using this strategy, doctors can monitor a patient's condition and determine the best course of therapy.

Our research focuses on precise results and data to evaluate experiment outcomes. A variety of models have been employed to test and process the optical disease data in order to achieve the best outcomes. The uniqueness is the use of different models on the same dataset, whereas earlier authors used fewer and fewer models compared to ours to obtain better outcomes in their experiment.

Artificial intelligence (AI)-based algorithms enhance search efficiency and offer fresh perspectives on data analysis^[6]. Automation of data gathering, synthesis of big data sets, optimization of research lab resources, and management of complicated data sets are only a few AI applications. It can also provide real-time assistance to manage massive, extended-duration learning sessions. In addition to the critical contributions indicated in the abstract, this study added a column to the OCID dataset that captures the etiology of eye illness, making this dataset available on Kaggle. Selecting the most important characteristics is crucial to enhancing feature extraction. Finding the best machine learning algorithm for categorizing the five causes of eye illnesses is preferable to using deep learning networks. Less computing power is needed for this method.

Apart from the benefits of utilizing AI in our study, there are some disadvantages. For example, the most widespread problem is that most contemporary AI systems can only evaluate one optical disease at a time, but the ability to test and evaluate multiple eye diseases is a significant issue. In addition, integrating eye clinicals with AI models for obtaining photos directly from patients would be a challenge, which would be extremely difficult to implement in our location due to a lack of understanding of AI and models.

Our paper has been organized into five major sections. The first two sections provide a straightforward introduction and a literature review. The final three sections address the methodology used to obtain results and outcomes acquired following experiments, followed by a discussion of the results and concluding with a conclusion.

2. Literature review

2.1 Introduction

Deep learning has shown tremendous potential in ophthalmology, particularly in the classification of ocular diseases. It has been used successfully in various imaging modalities, including

fundus photography, optical coherence tomography (OCT), and ultra-widefield imaging (UWF). Deep learning models have proven to be effective in detecting and classifying diabetic retinopathy, glaucoma, age-related macular degeneration (AMD), hypertensive retinopathy, and other ocular illnesses^[12]. The sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUROC) of these models are all very high. In several cases, they beat established machine learning classifiers and human experts. Deep learning algorithms have been utilized for lesion segmentation, diagnosis and classification, disease progression prediction, screening programs, image synthesis, image quality assessment, and ocular localization.

2.2 Related studies and findings

Diabetic retinopathy, glaucoma, and age-related macular degeneration are three of the most common and serious eye illnesses, and authors in^[9] have investigated a sophisticated deep-learning system that identifies all three. In addition, in^[2], researchers present a unique hierarchical deep learning network they developed to demonstrate the efficacy of a deep learning algorithm in diagnosing corneal disorders. The suggested model consisted of multi-task, multi-label learning classifiers representing a distinct stage in a hierarchical taxonomy of eye diseases. The proposed technique was trained from scratch using a historical dataset consisting of 5,325 photographs of the eye's surface. Further, using a massive database of images of the ocular surface, the scientists created a deep learning system that can accurately identify four prevalent corneal disorders. According to the research authors, the suggested model achieves 93% accuracy in testing, 88% accuracy in training, 93% accuracy overall, and 83% recall accuracy. Similarly, in^[11], the authors suggest a deep learning-based automated screening system that can identify and diagnose medical problems such as diabetic retinopathy, glaucoma, and age-related macular degeneration. Authors report the following findings from their experiment: a Cohen's kappa of 0. The five main forms of eye diseases included in the ocular disease intelligence recognition dataset will be used to test different machine learning models' abilities to diagnose visual impairment accurately. The result of this level of accuracy was a 99. For instance, the author of^[14] used three models to predict cataracts: CNN, Inception V3, and VGG-19. Eye infections were the focus of the research; many retinal diseases such as CNV, DRUSEN, AMD, and DME may be traced back to such damage. Another research has expanded on the many forms and categories of eye diseases to highlight the significance of early visual identification in preventing additional complications. The suggested method mainly aimed to diagnose eye diseases such as diabetic retinopathy, glaucoma, and cataracts. The Ocular Disease Intelligent Recognition dataset is then used to assess the efficacy of DeepRetino in production. In addition, the same area of eye detection issues and their categorization was the subject of another investigation. For instance, the suggested approach is used to assess the risks and benefits of cataract surgery for ageing eyes^[8]. It has been shown that algorithms and SVM classifiers can reliably diagnose these conditions using examples of ocular pathologies such as glaucoma, cataracts, the retina, and the fundus of a healthy eye. Their trial showed that the algorithms and their effectiveness set them apart from the competition; specifically, for a cataract-affected eye, the best results were

obtained using gradient boosting, which achieved an accuracy of 90%. For instance, the proposed weighted cost function is networked in an unbalanced data set consisting of fundus images with four classifications ('normal,' "cataract," "glaucoma," and "retinal illness").

2.3 Analysis and Discussion

Based on the evidence in the reviewed articles, deep learning models offer great potential for improving the screening and diagnosis of ocular diseases. They can provide faster and more accurate analysis of medical images compared to traditional methods. Deep learning algorithms can automate tasks such as lesion segmentation and disease classification with high levels of accuracy. It can help in reducing human error and improve efficiency in clinical practice. Furthermore, deep learning models have shown promise in predicting disease progression and assessing treatment outcomes. For instance, most of previous studies have shown that the dataset was balanced by utilizing the same amount of data for each class, and the classes were trained with the pre-trained VGG-19 architecture^[15]. Also, they started by importing the dataset and associated images into the model, using the same number of photos for both classes^[16]. The VGG-19 model was studied using the transfer learning method. After appropriately balanced the dataset, the accuracy of the individual classes improved. In addition, To train/validate/test our model, authors have used 3250 photos from seven public datasets. Approximately 6.95% of the images had age-related macular degeneration (AMD), 63.69% had diabetic retinopathy (DR), 5.26% had glaucoma, 8.82% had various retinal illnesses, and 15.28% had normal retina. For preprocesses, the CLAHE algorithm was used for image cropping and enhancement^[17]. They have also used data augmentation, such as image rotation and vertical and horizontal flipping. For various disease categorizations, the method applied an Efficient-Net B4 and B7 Convolution Neural Network (CNN) Ensemble with fine-tuning. Obviously, there are still challenges that need to be addressed before widespread implementation can occur^[18]. These include issues related to data availability (such as access to large annotated datasets), model interpretability (understanding how a deep learning model arrives at its decisions), validation against gold standards or expert consensus guidelines for disease severity grading or staging systems specific to ocular diseases, and the need for prospective clinical trials to evaluate the impact of deep learning models on patient outcomes. Furthermore, the effectiveness of multiple optimizers in identifying eye disorders is evaluated in previous work by utilizing a deep learning technique with a ResNet Convolutional Neural Network (CNN) paired with a Bidirectional Long Short-Term Memory (LSTM) network. Some Adagrad, FLTR, NADAM, and SGD were examined, and their performance in terms of accuracy and loss values was compared. In terms of accuracy, Adagrad beat the other optimizers, with an average of 95.3% versus Nadam (79%), FLTR (62%), and SGD (80%). All four optimizers, on the other hand, yielded relatively low loss values, indicating a good level of model convergence and stability. These findings shed light on optimizing optimizers in the context of eye illness categorization using deep learning algorithms. Overall, the weaknesses were data limitations in all previously related work and receiving a single result while applying deep learning models on multiple

images was noticed. The strengths were automated tasks and fast and accurate experimental results.

In conclusion, deep learning models have demonstrated significant potential in classifying ocular diseases. They offer faster and more accurate analysis of medical images compared to traditional methods. However, further research is needed to address the challenges associated with data availability, model interpretability, validation against gold standards or expert consensus guidelines, and prospective clinical trials. With continued advancements in deep learning technology and increased collaboration between ophthalmologists and computer scientists, these challenges can be overcome, leading to improved screening and diagnosis of ocular diseases.

3. Methodology

As mentioned in the introduction, the main contribution of this research is classifying the cause of eye disease. The methodology employed in this research consists of four stages: dataset pre-processing, feature extraction, feature selection, and classification and evaluation. Figure 1 illustrates the methodology used in this study. The original dataset was cleaned of missing or unreadable values and preprocesses techniques were applied. It included color adjustments, noise reduction, and image resizing. Subsequently, the dataset was optimized using feature selection techniques after entering the SqueezeNet deep learning model for feature extraction. The final stage involved the classification and evaluation of different classifiers using various metrics.

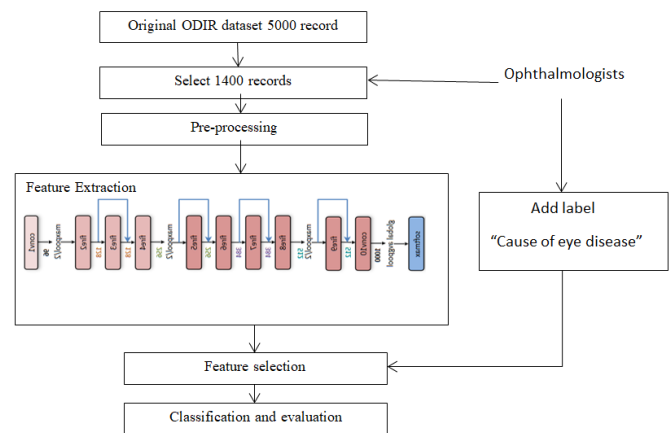


Figure 1: The methodology of the research.

3.1 Dataset preprocesses:

Ocular Disease Intelligent Recognition (ODIR) has been chosen in this research. The structured ophthalmic database contains data on 5,000 patients, including their age, color fundus photographs of both left and right eyes, and doctors' diagnostic keywords. The dataset is intended to reflect real-life patient information collected by Shanggong Medical Technology Co., Ltd. from various hospitals and medical centres in China. Fundus images were captured using Canon, Zeiss, and Kowa, resulting in varying image resolutions. Trained human readers labelled the annotations with quality control management. Patients were classified into eight categories: Normal, Diabetes, Glaucoma,

Cataract, Age-related Macular Degeneration, Hypertension, Pathological Myopia, and other diseases/abnormalities.

Despite the widespread use of this dataset in various research studies, one of the primary challenges associated with its use is the limited number of cases, which is only 5,000. The study's objective was to identify the main patient records that align with the objective of identifying the causes of these diseases by examining the data with the assistance of ophthalmologists.

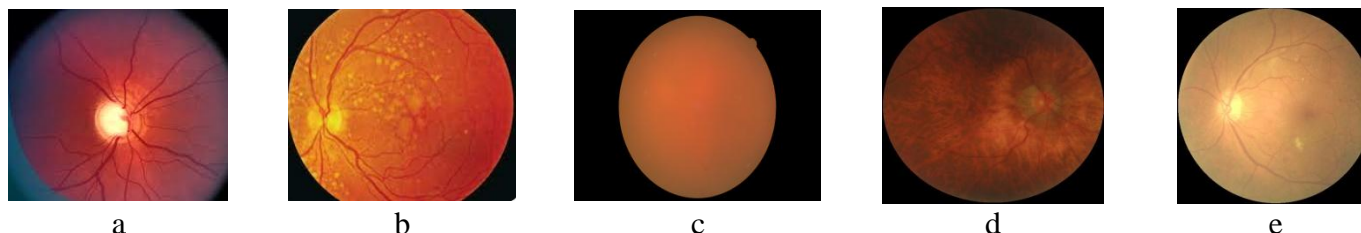


Figure 2: Random image in (ODIR) a) Glaucoma, b) Age-related Macular Degeneration, c) Cataract, d) Pathological Myopia, e) Other diseases/abnormalities.

3.2 Feature extraction:

The ODIR dataset comprises color fundus photographs of patients along with additional information such as age, sex, and disease type. However, this information alone was insufficient to accurately classify the type of disease. Therefore, a pre-trained deep learning model was employed to perform this task. Numerous techniques and pre-trained deep learning models are employed in various research studies for feature extraction. However, due to time constraints, we could not apply these techniques and compare their performance. SqueezeNet has been used in the feature extraction process. It is a valuable technique for reducing input data's dimensionality and improving downstream models' performance. The process involves using a pre-trained model to extract relevant features from input data, which can be used for classification. One thousand features have been extracted in this stage. The following steps are needed to use SqueezeNet for feature extraction:

1- Load the pre-trained SqueezeNet model: SqueezeNet has been pre-trained on large datasets such as ImageNet, meaning that it has already learned a set of features useful for a wide range of image recognition tasks.

2- Remove the final classification layer: The final layer of the SqueezeNet model is typically a classification layer that maps the extracted features to specific categories. Since we are using the model for feature extraction rather than classification, we removed this layer.

3- Pass the input data through the modified SqueezeNet model: Once we have removed the final classification layer, we pass the dataset through the modified SqueezeNet model to extract features. The model's output will be a set of feature vectors representing the input data.

The extracted features can be used as inputs for other models or tasks. A support vector machine (SVM) classifier or a neural network trained for a particular job might benefit from such data as inputs.

Ophthalmologists were consulted to identify ocular disease types, and a new column was added to the dataset labelled "cause of visual impairment" for use during the classification process. Diagnosing the causes of visual impairment was done by specialized doctors over seven days. Due to the complex nature of the work, only four specific reasons were selected, and 1,400 photographs and records were chosen for analysis. Figure 2 shows random images of eye disease.

3.3 Feature selection:

It refers to assessing the value of a set of attributes by analyzing each feature's independent predictive capability and the degree of duplication between them. Feature subsets with a strong correlation with the class while maintaining low inter-correlation is desirable. The search for attribute subsets involves using a greedy hill-climbing approach enhanced with a backtracking mechanism. The number of consecutive non-improving nodes allowed can be set to control the amount of backtracking done. A greedy hill-climbing strategy is a heuristic algorithm that seeks to achieve the optimal solution by consistently making the most favorable local improvement at each iteration, disregarding the global optimum or the possibility of backtracking. It is often used for optimization or search problems^[20].

On the other hand, the best-first method may begin with an empty set of attributes and search forward, start with a complete set of facts and search backwards, or initiate the search at any point and explore both directions by considering all potential single attribute additions and deletions at a specific topic. In this research, the best-first method was employed for feature selection to achieve the best classification accuracy and reduce implementation time.

3.4 Classification

After optimizing the extracted features, they will be considered an input classification process. The algorithms used in classification are Tree, Naive Bayes, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Ensemble. Of note, this study utilized a 10-fold cross-validation technique. This method is commonly employed in machine learning research to assess the generalizability

of a model and estimate its performance on unseen data. It has been shown to provide a more precise estimate of model performance than traditional training and testing techniques.

4. Results and Discussion

The effectiveness of several machine learning algorithms in performing classification is discussed. Initially, we computed the precision, recall and F1-score for the chosen models. However, these results were found to be very similar. Consequently, we

employed the accuracy metric to assess the performance of various algorithms in these models. Table 2 shows the precision, recall and F1-score of the selected models. MATLAB has been used in both feature extraction and classification. The dataset has been partitioned into ten folds to avoid overfitting, and each fold's accuracy has been estimated. Table 1 shows the accuracy of each algorithm, while Figure 3 shows the ROC of the model with the highest accuracy of each algorithm. ROC (Receiver Operating Characteristic) for validation data has been calculated. It is a helpful tool for evaluating a classifier's performance on a validation dataset and can help identify the best threshold for a given application.

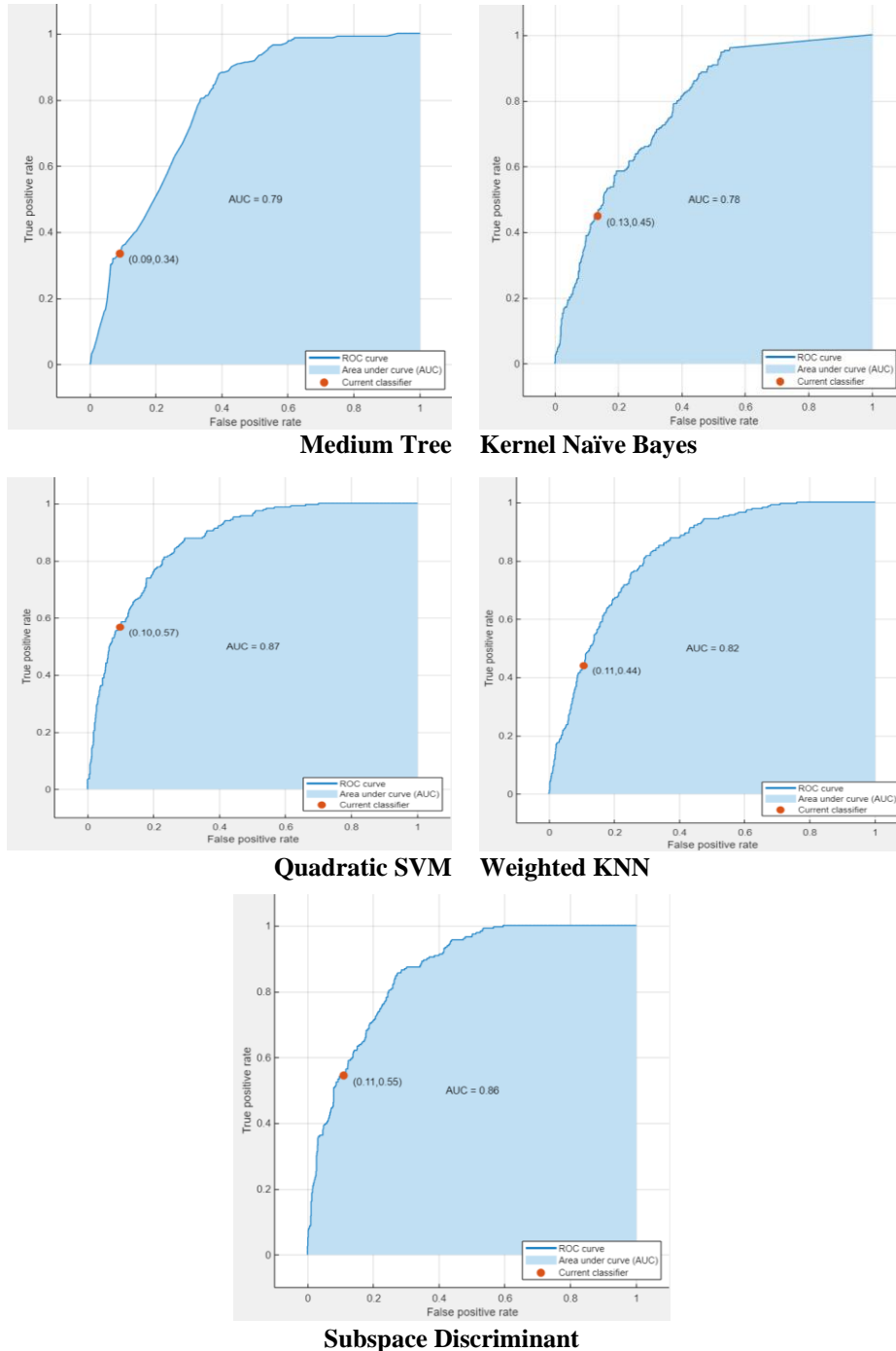


Figure 3: ROC and RCU values of the highest accuracy algorithm in each model.

Table 1: shows the algorithms and accuracy levels.

Algorithm	Model	Accuracy
Tree	Fine Tree	58.2%
	Medium Tree	63.6%
	Coars Tree	57.0%
Naive Bayes	Gaussian Naïve Bayes	62.8%
	Kernel Naïve Bayes	63.7%
SVM	Linear SVM	70.8%
	Quadratic SVM	71.3%
	Cubic SVM	69.6%
	Medium Gaussian SVM	69.8%
	Coarse Gaussian SVM	66.1%
KNN	Fine KNN	61.6%
	Medium KNN	66.1%
	Coarse KNN	64.1%
	Cubic KNN	65.7%
	Weighted KNN	66.3%
	Boosted Trees	65.0%
Ensemble	Bagged Trees	68.4%
	Subspace Discriminant	69.7%
	Subspace KNN	63.8%
	RUSBoosted Trees	63.4%

Table 2: The precision, recall and F1-score of selected models.

Model	precision	recall	F1-score
Tree	0.541	0.539	0.540
Naive Bayes	0.626	0.628	0.626
SVM	0.701	0.702	0.701
KNN	0.619	0.616	0.617
Ensemble	0.634	0.638	0.636

For instance, Quadratic SVM is a special case of SVM that employs a quadratic kernel function to differentiate across feature space classes.

The non-linear relationships between features and the objective variable make quadratic SVM a suitable contender for classifying eye diseases. Quadratic SVM can represent higher-order interactions between features, which is useful for capturing the complicated and non-linear correlations between symptoms, diagnostic tests, and disease severity common in ocular disorders. Moreover, SVMs are known for their ability to handle high-dimensional data, which is often the case in medical datasets with many different clinical and imaging features for each patient. Important characteristics for classification may be learned using the quadratic SVM, while irrelevant or irrelevant information needs to be addressed.

Finally, SVMs include an adjustable regularization value to prevent overfitting, which may be problematic in datasets with limited samples, such as those in the medical field. A model's ability to generalize to novel data may be compromised by its complexity.

Quadratic SVM is a useful method for classifying ocular diseases because it deals with multifaceted interactions between

characteristics and the target variable, robustness in the face of high-dimensional data, and resistance to overfitting.

Conclusion

This research aims to expedite the diagnosis of eye diseases and reduce the workload in ophthalmology clinics by utilizing machine learning to categorize the causes of eye impairment.

Most of the research in this field focused on classification the binary classification of eye disease or multi-classification in one kind of disease. In this research, we focused on the sort of cause instead of the condition. At the same time, we consider multi-classification in this research. The four primary causes are congenital, refractive error, ageing, and diabetes. Due to the close similarity of Fundus images and the overlap of symptoms between different diseases, the classification accuracy is low. This issue can be addressed by increasing the number of patient records. Additionally, incorporating patient history information can further improve the accuracy of classification. The findings demonstrate that extracting features using SqueezeNet and Quadratic SVM classifier outperforms Tree, Naive Bayes, KNN and Ensemble for the ODIR dataset. Quadratic SVM verified 8% more accuracy than Tree and Naive Bayes. As well as 5% more accuracy than KNN, and 2% more than Ensemble. In future studies, additional classifiers will be employed and compared. Local data will also be collected in this field as we believe each country has different types of eye diseases and different factors that cause these diseases.

Conflict of interests

None

Author Contribution

In this study, Ari Taha Guron, Mardin Abdullah Anwer, and Sazan Kamal contributed equally in conceptualizing the research project, designing the methodology, implementing and analyzing the results, and writing the manuscript. The author and ophthalmologist, Sami J. Abdulsamad, had a great role in cleansing the dataset and diagnosing diseases.

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