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Ocular Disease Classification Using Different Kinds of Machine Learning Algorithms

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Ocular disease is a term used to describe a wide range of illnesses that affect the eyes and visual system. These diseases can affect one or both eyes and can range from mild to severe. The use of machine learning algorithms to categorize ocular diseases has become an area of interest in the ophthalmology community.
This study is to compare the performance of different machine learning algorithms in classifying ocular diseases based on fundus images. The dataset of fundus images of patients diagnosed with different ocular diseases like Cataracts, pathological myopia, glaucoma, age-related macular degeneration, and abnormalities are considered. Ocular Disease Intelligent Recognition (ODIR) has been used. The SeequzeNet and GoogleNet deep learning models with different machine learning algorithms employed in experimental work includes KNN, random forest, support vector machines, logistic regression, and gradient boosting. The performance of each algorithm is evaluated using accuracy, sensitivity, and specificity metrics. The results show that logistic regression outperforms the other algorithms in terms of accuracy, sensitivity, and specificity. The findings of this study suggest that machine learning algorithms, particularly Logistic Regression, can be useful in accurately classifying ocular diseases based on fundus images. Feature extraction using SeequzeNet achieved an accuracy of 71.6%, outperforming GoogleNet's accuracy of 68.2%.

1. Introduction

In particular in ophthalmology, artificial intelligence (AI) has completely changed the field of medical diagnosis and management. By quickly and accurately evaluating massive amounts of data, it has made a significant difference in the detection and diagnosis of ocular illnesses. Early detection and precise classification of ocular diseases have become possible through the utilization of AI algorithms. Recent studies have demonstrated the potential of AI in ocular disease classification.

For example, a study published in the Journal of Glaucoma showcased a deep learning algorithm achieving an impressive accuracy of 96.7% in distinguishing between glaucoma and normal eyes (Medeiros FA, 2021). Similarly, in the British Journal of Ophthalmology, another study achieved an accuracy of 90.5% in classifying diabetic retinopathy using AI (Ttufail et al., 2020). These developments are serious because eye illnesses are a major global public health concern, and effective treatment depends on early detection and precise diagnosis. For the categorization of ocular diseases, a variety of machine learning methods have been used, including K-Nearest Neighbors (KNN), Random Forest, Support Vector Machines (SVM), Logistic Regression, and Gradient Boosting. For feature extraction, deep learning techniques like Convolutional Neural Networks (CNN) have been used. The effectiveness of these algorithms in categorizing pathological myopia, age-related macular degeneration, glaucoma, cataracts, and other anomalies has been assessed in several studies. For instance, Sharmila et al. (2020) classified diabetic retinopathy using a CNN and had a 94.5% accuracy rate. A decision tree method was used in a different study by Cheng et al. (2014) that produced results for the classification of glaucoma. This research is divided into six sections and organized as follows:. The first section is an introduction. Litertrue review on ocular disease classification is on section two. Section three explains the machine learning algorithms used in this research. The methodology is explained in section four. Section five illustrates the results. While the conclusion is stated in chapter six.

2. Literature Review

In recent years, the application of deep learning algorithms for the detection of various eye diseases has gained significant attention. Researchers have conducted several studies focusing on the use of deep learning techniques in this domain. Here, we will discuss some recent studies in this field. Naithani et al. (2019) proposed a deep learning-based system for the detection of diabetic retinopathy in fundus images. Their model consisted of two components: a segmentation network to identify the regions of interest and a classification network to classify the severity of the disease. The model achieved an impressive accuracy of 95.4% in detecting diabetic retinopathy, demonstrating the potential of deep learning in the diagnosis of this condition. Another study by Masood et al. (2019) presented a deep learning-based approach for the automated detection of glaucoma using optical coherence tomography (OCT) images. Their model consisted of a segmentation network to extract the optic disc and cup regions, followed by a classification network to predict the presence of glaucoma. The proposed approach achieved an accuracy of 93.2% in detecting glaucoma, outperforming traditional methods. Furthermore, He et al. (2022) conducted a study focusing on the detection of age-related macular degeneration (AMD) in OCT images using a deep learning-based system. The proposed model utilized deep learning techniques to accurately identify AMD in OCT images. These studies highlight the potential of deep learning algorithms in the automated detection of various eye diseases, including diabetic retinopathy, glaucoma, and age-related macular degeneration. The use of deep learning techniques has demonstrated promising results, showcasing the effectiveness of these methods in improving the accuracy and efficiency of disease detection in the field of ophthalmology.The proposed model consists of two parts: a segmentation network to extract the macula region and a classification network to predict the presence of AMD. The model achieved an accuracy of 92.3% in detecting AMD, demonstrating the potential of deep learning in diagnosing this disease. In (Wang et al, 2018) the researchers proposed a deep learning-based system for the automated screening of retinopathy of prematurity (ROP) using fundus images. The proposed model consists of a segmentation network to extract the blood vessels and a classification network to predict the presence of ROP. The model achieved an accuracy of 95.2% in detecting ROP, outperforming the traditional methods. Several studies have used machine learning algorithms for binary ocular disease classification. In this research, the accuracy of different kinds has been used machine learning algorithms in the Ocular Disease Intelligent Recognition (ODIR) dataset that consists of five types of disease and each disease consists of a different disease. For example, (Wensheng et al.,2019) used a random forest algorithm to classify glaucoma images into three categories. While in our research all these categories are under glaucoma disease images. Building upon the work of (Liu et al., 2022), who employed a convolutional neural network (CNN) for retinal disease classification from OCT images; this study investigates the performance of different feature extraction methods. The key findings of these studies have been summarized in Table 1.

Table 1 Summary of studies on ocular disease binary classification using machine learning algorithms, ROCT: Retina OCT, DR: Diabetic retinopathy, ARM: Age-related macular degeneration, G: Glaucoma, RVS:Retinal vessel segmentation

Study	Dataset	Algorithm	Accuracy	AUC
Liu et al. (2022)	ROCT	CNN	99.2%	0.999
Rasheeed et al. (2020)	DR	SVM	92.5%	-
Ieng et al. (2023)	ARM	CNN	96.3%	0.994
Cheng et al. (2020)	G	RF	96.4%	0.983
Wu et al. (2018)	RVS	FCN	96.4%	-

2.1 K-Nearest Neighbors

It is considered a supervised machine learning algorithm and is regularly used for classification and regression tasks. The fundamental principle behind K-NN involves identifying the k closest neighbors of a given data point and making predictions based on the labels or values associated with those neighbors. For classification, the predicted label of a data point is determined by a majority vote among its k nearest neighbors, while for regression, the predicted value is computed as the average of the values from its k nearest neighbors (Alpaydin, 2010).

When working with K-NN, the selection of the k value is a crucial hyperparameter. Choosing a smaller k may lead to overfitting, where the model becomes excessively sensitive to noise in the data, while opting for a larger k may result in underfitting, where the model oversimplifies the underlying patterns. Additionally, the choice of distance metric used to measure the similarity between data points can significantly impact the algorithm's performance.

K-NN is appreciated for its simplicity and ease of implementation. However, it can be computationally demanding when dealing with large datasets. Moreover, K-NN assumes uniform data distribution and may not perform well when confronted with high-dimensional datasets (Hastie et al., 2009).

2.2 Random Forest

Random Forest is a supervised machine learning algorithm that is employed for classification and regression tasks. It operates as an ensemble method, utilizing multiple decision trees to enhance the accuracy and resilience of the model's predictions. In a Random Forest, each decision tree is constructed using a randomly selected subset of the training data and a randomly chosen subset of the features (Breiman, 2001). This randomness aids in mitigating overfitting and improving the model's ability to generalize to unseen data.

For classification, the Random Forest predicts the label of a data point by aggregating the majority vote from all the decision trees in the forest. In regression tasks, the Random Forest predicts the value of a data point by averaging the predictions from all the decision trees in the forest.

Random Forest is a potent and widely utilized algorithm that can handle both categorical and continuous features. It also has the ability to manage missing values and outliers effectively. Additionally, Random Forest exhibits robustness to noise and performs well with high-dimensional data. However, due to the use of multiple decision trees, it can be computationally demanding and may not be suitable for real-time applications (Hastie et al., 2009).

2.3 Support Vector Machines

Support Vector Machines (SVM) is a highly influential machine learning algorithm utilized for classification and regression tasks (Vapnik, 1995). It was initially introduced by Vladimir N. Vapnik and his team in 1992, and has since gained significant popularity due to its efficacy in handling high-dimensional and non-linear datasets. In essence, SVMs seek to identify an optimal boundary, known as a hyperplane that effectively separates distinct classes within a dataset. The SVM algorithm strives to maximize the margin between the hyperplane and the nearest data points from each class, which are referred to as support vectors. These support vectors play a critical role in determining the final hyperplane (Cortes and Vapnik, 1995).

SVMs encompass various variants, including linear SVMs, non-linear SVMs, and kernel SVMs. Linear SVMs are suitable for linearly separable datasets, identifying a hyperplane that separates the data points into different classes. Non-linear SVMs address non-linear datasets by transforming the data into a higher-dimensional space, where the data points can be linearly separable. Kernel SVMs extend the capabilities of non-linear SVMs by enabling more complex data transformations (Shawe and Cristianini, 2004).

SVMs have found successful applications in diverse fields, such as image classification, text classification, and bioinformatics. They have also been employed for anomaly detection, clustering, and feature selection (Kecman, 2001). SVMs are highly regarded for their ability to handle complex data patterns and high-dimensional spaces, making them a valuable tool in various domains.

2.4 Logistic Regression

Logistic regression is a statistical algorithm widely used for binary classification tasks, such as determining if an email is spam or not or predicting if a customer will make a purchase (Hosmer et al., 2013). It models the probability of a binary outcome by fitting a sigmoid curve to the data. The sigmoid function maps input values to probabilities between 0 and 1, representing the likelihood of the positive class. In logistic regression, the input features are multiplied by weights, and a bias term is added (Bishop, 2006). The resulting linear combination is then passed through the sigmoid function to obtain the predicted probability.

The model is trained by minimizing a cost function that penalizes incorrect predictions. This optimization problem can be solved using techniques such as gradient descent or other optimization algorithms (Goodfellow et al., 2016). Logistic regression is favored for its simplicity, interpretability, and effectiveness across various practical applications. It can also be extended to handle multi-class classification problems by utilizing methods like one-vs-all or softmax regression (Hastie et al., 2009).

2.5 Gradient Boosting

It is a powerful machine learning algorithm for both regression and classification tasks. It works by building an ensemble of weak learners in a stepwise manner, with each new learner trying to improve the mistakes made by the previous learners (Friedman, 2001). The final prediction is obtained by aggregating the predictions of all the learners. The key idea behind gradient boosting is to fit each new learner to the residual errors made by the previous learners (Chen and Guestrin, 2016). This is done by optimizing a loss function that measures the difference between the predicted and actual values. The gradient of the loss function is then used to update the weights of the weak learner, in a way that minimizes the loss. There are many variants of gradient boosting, including the popular XGBoost and LightGBM libraries (Ke et al, 2017). These libraries use various optimizations and techniques to make the algorithm more efficient and scalable, such as parallelization, feature subsampling, and tree pruning. Gradient boosting has been successfully applied in many domains, such as online advertising, recommender systems, and fraud detection. It has also won several machine learning competitions and is considered one of the most powerful algorithms in the field.

2.6 Sequeez Net

SqueezeNet was released by (Iandola et al., 2016) with fewer parameters and high accuracy while broadly exploring the design space of CNN architectures. (Han et al., 2016) have experimented further with SqueezeNet and model compression. They designed a new approach called Dense-Sparse-Dense (DSD).
It used model compression during training as a regularize to improve accuracy, producing a compressed set of SqueezeNet parameters that is 1.2 percentage-points more accurate on ImageNet-1k, and also producing an uncompressed set of SqueezeNet parameters that is 4.3 percentage-points more accurate, compared to (Iandola et al., 2016) results. In 2017 the same authors improved it with a CNN architecture with 50×fewer parameters than AlexNet and maintained AlexNet-level accuracy on ImageNet (WU et al., 2017). Because small models are more amenable to onchip implementations on FPGAs, (Gschwend, 2016) developed a variant of SqueezeNet, implemented it on an FPGA, stored the parameters of a SqueezeNet-like model entirely within the FPGA and eliminated the need for 23 off-chip memory accesses to load model parameters. Figure 1 shows the architecture of the model.

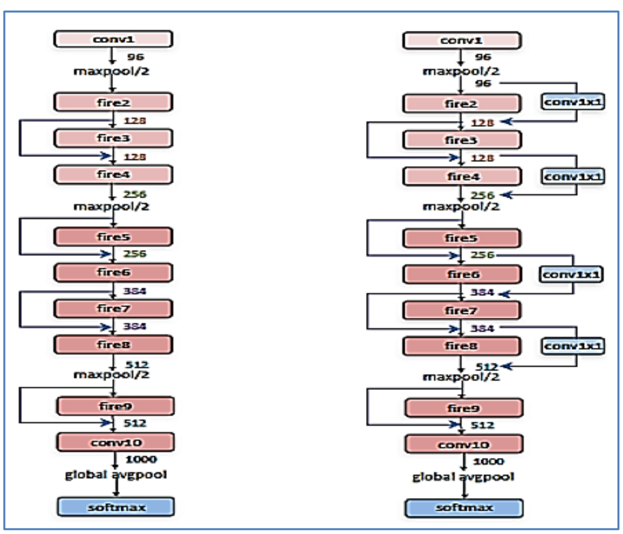


Figure1 Left: SqueezeNet with simple bypass, Right: SqueezeNet with complex bypass (Iandola et al., 2016).

2.7 GoogleNet

GoogleNet is the first architecture that uses a more complex architecture with several network branches in 2015. One of the best models in the ILSVRC'14 competition achieved an error rate of 6.7% on the classification task. However, GoogleNet is commonly known as "Inception Network" because the basic building block is arranged as an Inception module. The processing in GoogleNet occurs in parallel. It means that all the necessary processing blocks are parallel and combine their output feature representations. However, concatenating all the individual feature representations from each block along the depth dimension causes a very high-dimensional feature output problem. A giant network can be created by stacking multiple inception modules together. GoogleNet uses a global average pooling followed by a fully connected layer toward the network's end for classification. The global average pooling layer provides faster computations with better classification accuracy and a much-reduced number of parameters (Szegedy et al., 2015). Figure 2 shows GoogLeNet Inception Module (Prabhu,2018).

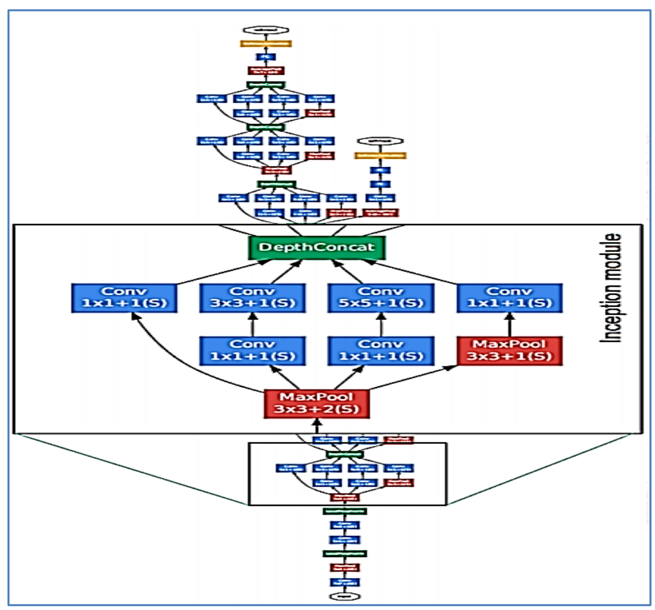


Figure 2 GoogLeNet Inception Module (Prabhu,2018).

3. Methodology

The classification of eye diseases using different kinds of machine learning algorithms has been achieved through the following methodology which is illustrated in Figure 3.

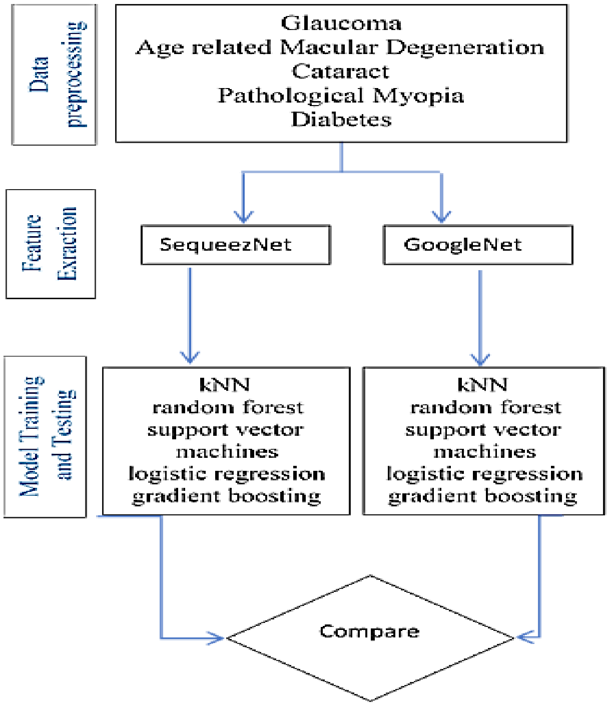


Figure 3 The Methodology used in the research

Figure 4 illustrate a segment of the program extracting features from the image of ocular diseases from the dataset to create another dataset of features instead of images. The feature can be fed to any of these classification methods to give us the result. The features in this work are saved as CSV file to be fed to Weka software for classification.

```
k=1;
OD=dir ('E:\Dataset\ Ocular Disease \');
ODSIZE= size(OD,1);
des11(ODSIZE,1)=0;
for i=1: ODSIZE
i
Im= imread([' E:\Dataset\ Ocular Disease /IMG-
',num2str(i),'.jpg']);
[im1, des1, loc1]=extract_features(Im);   ///  this
is to extract features from the image
ODfeaturelabel=[['  E:\Dataset\  Ocular  Disease
feature/'],int2str(k)];
save (ODsiftlabel,'im1', 'des1','loc1') ;
 k=k+1:
```

Figure 4 illustrate a segment of the extracting features program

This file has been processed to index the attributes of the feature vectors in addition to ad class labels to each vector which are represented here by the Ocular disease class

3.1 Dataset

There are two methods of imaging used as diagnostic methods in ophthalmic practice: fundus digital photography and optical coherence tomography (OCT). In this research fundus digital photography has been involved in collecting a diverse range of images for training and testing.

Deep learning has showed tremendous potential in ophthalmology, particularly in the classification of ocular diseases. It has been used successfully in a variety of imaging modalities, including fundus photography, optical coherence tomography (OCT), and ultra-widefield imaging (UWF). It has proven to be effective in detecting and classifying diabetic retinopathy, glaucoma, age-related macular degeneration (AMD), hypertensive retinopathy, and other ocular illnesses (Ting etal, 2018). However, it needs expensive recourse and computation. In this research fundus digital photography has been involved. Deep learning modle has been used in features extraction while different machine algorithems were used in classification.

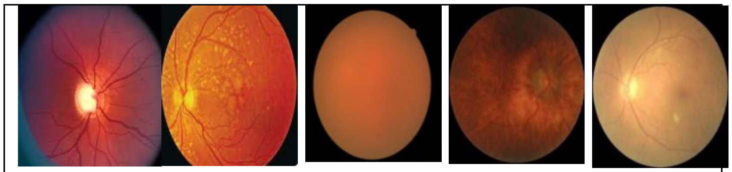
The Ocular Disease Intelligent Recognition (ODIR) dataset, which contains fundus images of 5,000 patients with different types of eye diseases, is presented as an example of such a dataset. The dataset was collected from various hospitals in China and manually labeled with eight different disease labels. Annotations were provided by trained human readers with quality control management (Kaggle.com). The dataset consists of eight labels which are: Normal, Diabetes, Glaucoma, Cataract, Age-related Macular Degeneration, Hypertension, Pathological Myopia, and Diabetes. Table two below shows the five types of diseases used in this research.

Table 2 ODIR dataset applied in this research. PM:Pathological Myopia, ARM:Age-related macular egeneration, G:Glaucoma, C:Cataract, D:Diabetis

	G	C	PM	ARM	D
No of Participants	300	300	300	300	300
Female	158	154	130	119	143
Male	142	146	170	181	157
Age	45- 65	45- 65	45- 65	45- 65	45- 65

3.2 Data preprocessing

All images in the dataset have been resized and the pixel values have been normalized as preprocessing stage to prepare it for training. Figure 5 shows random images of ODIR.



a b c d e

Figure 5 Random image in (ODIR)
a) Glaucoma, b) Age related Macular Degeneration, c) Cataract, d) Pathological Myopia, e) Diabetes

3.3 Feature extraction

In this step SqueezeNet and GoogleNet deep learning models have been used to extract the features from the images. SqueezeNet is a deep learning architecture that has been designed to achieve high accuracy while using significantly fewer parameters than traditional neural networks (WU et al., 2017).

This makes it an excellent choice for feature extraction, especially in cases where limited computational resources are available (Gschwend, 2016). In contrast to the SqueezNet, the complete inception module in GoogleNet, performs dimensionality reduction before passing the input feature volume through the 3x3 and 5x5 convolution filters to avoid a high-dimensional feature output problem. This dimensionality reduction is performed using a fully connected layer equivalent to a 1x1 dimensional convolution operation (Szegedy et al., 2015).
By using a combination of convolutional layers and fire modules, SqueezeNet can extract meaningful features from images while minimizing the number of parameters needed to do so. This not only reduces the computational complexity of the model but also helps prevent overfitting, which is a common problem in deep learning. Moreover, SqueezeNet has achieved state-of-the-art performance on several benchmark datasets, including ImageNet, CIFAR-10, and CIFAR-100, while using significantly fewer parameters than competing models. This makes it an attractive choice for researchers and practitioners who are looking to achieve high accuracy with limited computational resources.

3.4 Model Training and Testing

After preprocessing the dataset and extracting the features, the subsequent phase involves training various machine learning algorithms using the prepared data. The percentage of the training dataset was 70% because
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.
the main purpose of training is to enable the algorithms to learn and identify various types of eye diseases by examining the distinctive features that have been extracted in the images.
Once the algorithms have completed the training process, they need to be tested to assess their performance and effectiveness. This evaluation is typically conducted using a distinct dataset of images that the algorithms have not encountered during training, thus ensuring an unbiased assessment.
To measure the accuracy of the algorithms, various metrics can be employed, including precision, recall, and F1 score. Precision assesses the proportion of correctly identified positive cases out of all cases predicted as positive. Recall, also known as sensitivity or true positive rate, measures the proportion of correctly identified positive cases out of all actual positive cases. The F1 score is a harmonic mean of precision and recall, providing a balanced assessment of the algorithm's performance. These metrics help quantify the algorithms' ability to accurately detect and classify eye diseases based on the provided image features.

4. Results and discussion

Five types of experiments have been conducted to check the accuracy performance of the classification of ocular diseases. These types are KNN, SVM, Random Forest, Logistic Regression, and Gradient Boosting. Each algorithm has its own strengths and weaknesses, and its performance may vary depending on the specific dataset and experiment setup. The experimental work is conducted to test the accuracy of these algorithms by working on the data set of ocular diseases. The features were extracted and prepared. The size of each features vector was extracted is 1000, it was used to express different ocular diseases of the environmental eye diseases namely. To demonstrate the accuracy performance of each one, the algorithm was implemented on the dataset each grwas oup divided into two parts, train and test images. Different running tests were used 10 times.

The algorithm's ability to make classification was assessed using several metrics, including sensitivity, specificity, and accuracy. In addition, Receiver Operation Characteristics (ROC) curves were generated, and the area under the ROC curve (AUC) was calculated. The ROC curve is a graph that displays the relationship between the true positive rate (sensitivity) and the false positive rate (1-specificity) at various decision thresholds. AUC was measured to determine how well the classifier was able to differentiate between different classes. The prediction accuracy increased as the curve approached the upper left corner of the graph. A value of AUC equal to 1 or 100% indicated a perfect prediction, while 0.5 or 50% represented a poor prediction. The results of AUC show that the curve of SVM, Logistic Regression and Gradient Boosting are close to one and very close to each other. However, AUC of kNN and Random Forest are similar.Matalb 2021b has been used in extracting feature processes, while orange has been used for assessing the classifiers.

Table 3 shows the results of the classification for KNN, SVM, Random Forest, Logistic Regression, and Gradient Boosting approach implemented on the data set using WEKA software.

It is essential to note that the images of the funds bear a striking resemblance to one another, and they may share common characteristics.

Table 3 the evaluation results of different ML algorithms

Algorithm		KNN	SVM	Random Forest	Logistic Regression	Gradient Boosting
SqueezeNet	AUC	0.878	0.918	0.872	**0.92**	0.872
	CA	0.632	0.69	0.641	**0.71**	0.69
	F1	0.634	0.69	0.641	**0.71**	0.69
	Precision	0.645	0.691	0.643	**0.71**	0.691
	Recall	0.632	0.69	0.641	**0.71**	0.69
GoogleNet	AUC	0.858	0.913	0.85	**0.915**	0.896
	CA	0.597	0.669	0.594	**0.682**	0.65
	F1	0.597	0.663	0.591	**0.679**	0.65
	Precision	0.604	0.665	0.589	**0.677**	0.651
	Recall	0.597	0.669	0.594	**0.682**	0.65

The performance of the logistic regression is more than other classifiers; therefore the logistic regressionis is adapted in the second experiment for the classification process. Figure 6 shows the ROC curves.

The ROC curve illustrates a potential trade-off between accuracy and error rates for the specified class and provides a summary value (0 to 1). It is an analysis of the entire data set, including comparisons between the Ocular Diseases; and the Roc curve of classes of diseases for the two models used Googlenet and Seqeeznet.

These results show the tremendous potential of AI in the field of ophthalmology and suggest that AI algorithms could help improve the accuracy and speed of diagnosis, leading to more effective treatment and management of ocular diseases.

Overall, the results and performance of KNN, SVM, Random Forest, Logistic Regression, and Gradient Boosting algorithms for ocular disease classification using the ocular dataset may vary depending on the specific experiment setup and dataset used. However, all of these algorithms can achieve high accuracy and precision in classifying different types of ocular diseases and can be useful tools for automated diagnosis and screening of ocular diseases.

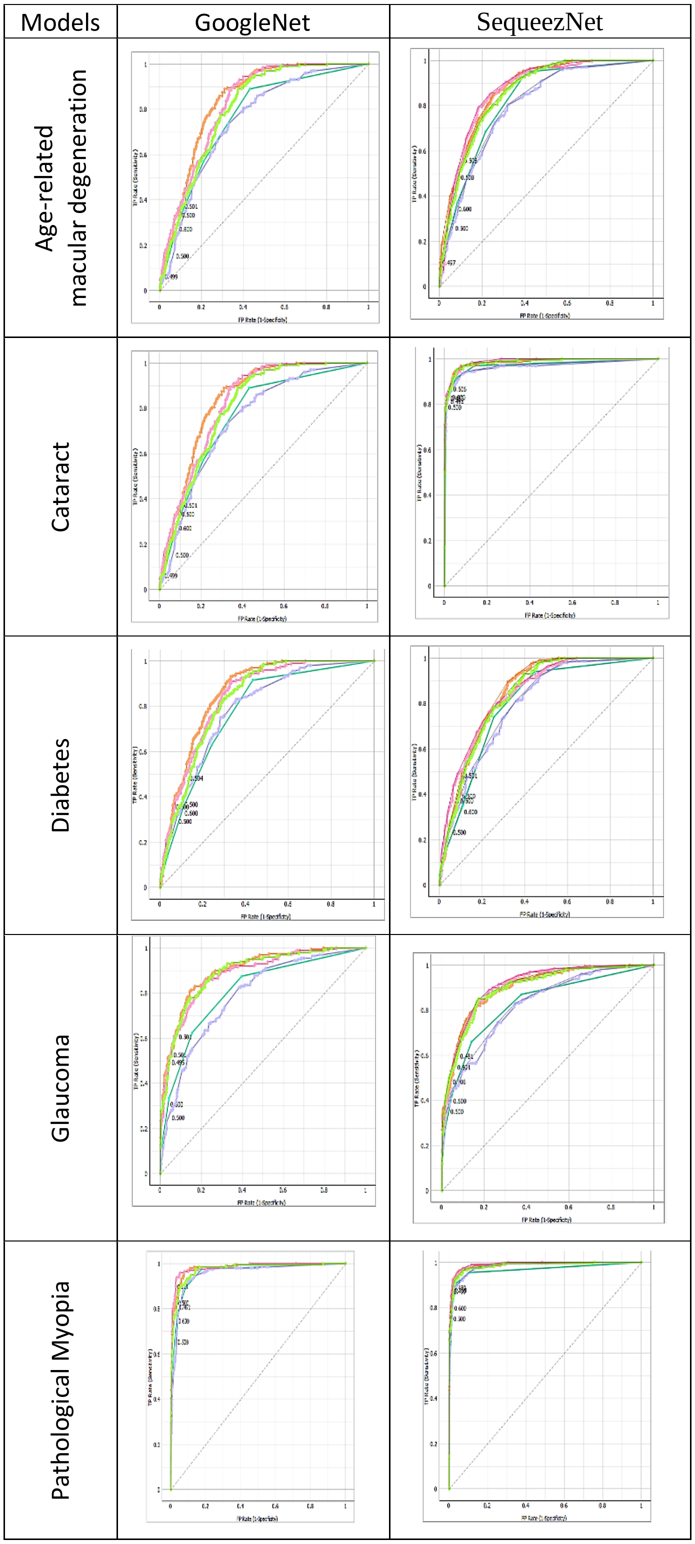


Figure 6 Random image in (ODIR) a) Glaucoma, b) Age related Macular Degeneration, c) Cataract, d) Pathological Myopia, e) Diabetes

The two models' SqueezeNet and GoogleNet performance are evaluated using the ROC performance for each category. The ROC curve is calculated for the ocular disease classification task using a method's ranked output. According to Figure 6, the ROC of Squeeze Net for the ocular disease class is based on KNN, SVM, and Random Gradient, the same procedure was done with Google Net. The average accuracy reached to 71.6% for Sequezeneet, 68% for GoogleNet.

5. Conclusion

In conclusion, five different kinds of eye diseases have been classified using different kinds of machine learning algorithms. Deep learning techniques have shown great potential in extracting the most important features of various eye diseases from the ODIR dataset. GoogleNet and SqueezeNet's compact architecture, high accuracy, and low computational requirements make it an excellent choice for feature extraction in deep learning models. The diseases that have been classified are glaucoma, age-related macular degeneration, pathological Myopia, cataract and Diabetes. The results suggest that deep learning-based approaches for feature extraction combined with Gradient Boosting classifier could be useful in improving the accuracy and efficiency of eye disease diagnosis, potentially leading to better patient outcomes. It has shown great potential in the accurate and efficient classification of ocular diseases. The development of such models can greatly improve the diagnosis and treatment of ocular diseases in the future.

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