EMPIRICAL EVALUATION OF EYE DISEASE DETECTION THROUGH MACHINE LEARNING TECHNIQUES

Manoj Kumar Bonu
dept. of Computer Science(Masters)
University of Central Missouri
Mxb07130@ucmo.edu

Kishore Simhadri
dept. of Computer Science(Masters)
University of Central Missouri
Kxs97760@ucmo.edu

Ravali Budidhi
dept. of Computer Science(Masters)
University of Central Missouri
Rxb73550@ucmo.edu

Dhheeraj Boleenenni
dept. of Computer Science(Masters)
University of Central Missouri
Dxb79090@ucmo.edu

ABSTRACT—
Treating the underlying eye illnesses would create a substantial piece of the road for humanity to finally arrive in the land of h appiness. Several visual illnesses, including cataracts, trachoma, and corneal ulcers, could trigger severe issues. Especially when these vision illnesses are effectively identified at a young age, could growth be stopped? Some eye illnesses have quite different, visually discernible signs. To accurately diagnose eye illnesses, examining a broad range of symptoms is vital. Since early detection of this disease is critical, once it has progressed to the point of irreversible vision loss, regaining vision becomes an impossible task. It is believed that a diabetic lesion is caused by a burst of the choroidal optic nerve, which results in the growth of an extra substance that is not cancerous in nature. Consequently, there are many different types of eye diseases, and identifying the damage to the retina in the eyes takes time. We, as humans, tend to overlook another developing disease in the eye. In this study, we suggest a unique method for automatically identifying eye diseases based on their visually discernible characteristics, using machine learning techniques and algorithms like support vector machines (SVM), logistic regression, the Naive Bayes classifier, and the decision tree algorithm. For effective feature extraction, we have used gray-scale scaling techniques so that RGB values have been neutralized. The suggested technique effectively distinguishes all ulcers that are presented in the facial image. As the ulcers are divided into three types, i.e., macro, micro, and no ulcer, The experimental results show that the SVM model outperforms all other algorithms used here. We contrast our approach with a few others that are already in use. Comparing our method to other methods, we can see greater accuracy. The SVM model has an overall prediction accuracy of 75.97%, whereas other algorithms are way less accurate than this rate. So, here we are suggesting the SVM model for the prediction of eye diseases.

Keywords— corneal ulcers, choroidal optic nerve, machine learning techniques, support vector machine, Naïve Bayes.

I. INTRODUCTION

When eye disorders go unnoticed during the initial stage, they might result in a partial or even complete loss of vision. Visual degradation can be avoided with early identification of various eye conditions. To produce the best and most accurate findings, machine learning approaches are now often employed for automatic illness detection, assessment, and clinical decision-making processes. Numerous difficult problems, including brain tumor segmentation with neuroimaging (MR), age-related eye illnesses, eye tumor identification, dermatological diagnostics, and computerized diabetic retinopathy screening, have been solved with the aid of machine learning algorithms. Despite their awareness, images are one of the most utilized variables in everyone's life, from the minute they wake up to the moment they shut their eyes. Constantly capturing images in our brains and analyzing those images will lead to the identification of an item and its current activity. We have used machine learning techniques to identify whether the image of the human eye contains corneal ulcers or not, and it predicts at the micro or macro level. In this technique, we achieve end-to-end training and testing datasets by providing the fundus picture (photography of the back of the eye) as input and getting the output as an outcome based on the model determination. Glaucoma is a disease that occurs when there is damage to the optic nerve of the human eye. Glaucoma is caused by high pressure in the blood vessels surrounding the eye, which results in blindness in the affected eye.

Remote image capture and diagnostics are expensive and infrastructure intensive. With advances in technology and image processing, it is feasible to automate disease identification and refer patients to doctors for additional evaluation. Several clinical decision support systems, employing breakthroughs in digital image processing and machine learning, have been created specifically to identify diabetic retinopathy and age-related macular degeneration. Although several of these systems outperform human specialists in terms of performance, they are each trained to identify a specific retinal illness. Because the early discovery of this condition is crucial, restoring eyesight becomes difficult after it has advanced to the point of permanent visual loss. A diabetic lesion is thought to be formed by a rupture of the choroidal optic nerve, which leads to the formation of an additional material that is not malignant. As a result, there are several forms of eye disorders, and determining the damage to the retina in the eyes takes a long time. As humans, we tend to ignore another growing eye illness.

Machine learning algorithms study data in order to identify underlying patterns without being told where to search. ML is rapidly being used in disease diagnosis. These software algorithms detect patterns and characteristics in pictures at various levels and link them to a recognized class of disorders. According to the scientific literature, supervised learning is now employed for the early identification and categorization of eye illnesses such as cataracts, conjunctivitis, and diabetic retinopathy. We describe various research findings in the section on related work where machine prediction is equivalent to that of human specialists for certain eye conditions.

Pictorial representation of our project:

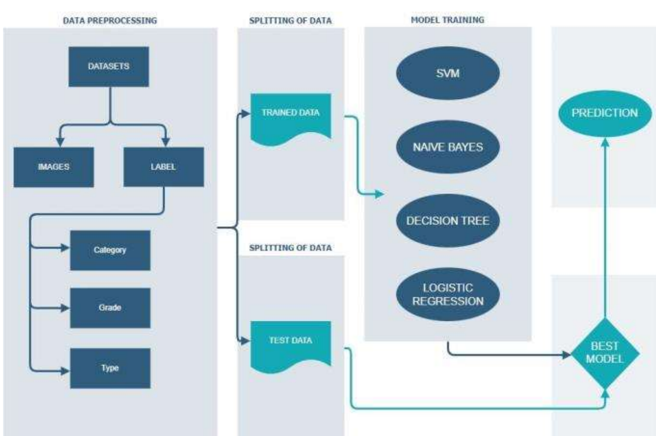

Fig1. Representation

This paper has been broken into six pieces for your convenience. In Section I, we provide an overview of the subject matter. Section II provides the main contributions and objectives. Section III contains work-related things. Section IV presents a summary of our findings and the procedure or algorithms which are used in the project. Section V contains the data sets and deep classification of the data. Results, the Acknowledgement section, and the future work were presented in Section VI.

II. MOTIVATION

Vision is considered one of the most crucial human senses, and its absence may have an impact on a person's creativity and autonomy. Millions of individuals are affected by retinal illnesses, which can lead to visual loss if not recognized and treated early. Retinopathy, age-related macular degeneration, glaucoma, and other retinal illnesses are examples. Early therapy approaches may be able to cure or delay the onset of the condition. Patients who are treated will have several extra years of vision. Even though there are many hospitals and eye clinics in India's cities, the doctor-to-patient ratio remains low. Several clinical decision support systems employing breakthroughs in digital image processing and automated intelligence have been created specifically to identify diabetic retinopathy and age-related macular degeneration. Although several of these systems outperform human specialists in terms of performance, they are each trained to identify a specific retinal illness. Many of these models use the retinal picture to identify, extract, and evaluate disease-specific characteristics. This necessitates a thorough understanding of the illness as well as considerable work in developing the characteristics for the classifiers. There is a paucity of both infrastructure and ophthalmologists in remote locations. A machine learning study has recently focused on identifying disorders such as diabetic retinopathy by collecting characteristics and then categorizing images. Our objective in this study is to reliably distinguish photos with retinal abnormalities from those with healthy retinas without using any intentional segmentation or object recognition. We instead employ a deep learning algorithm to categorize each fundus image's picture as healthy or sick. The network's design is both simple and quick. The method was assessed on two datasets, one of which included genuine patient retinal fundus pictures taken from a nearby hospital. Because early detection of this disease is critical, regaining vision becomes impossible once it has progressed to the point of irreversible vision loss. The diabetic lesion is thought to be caused by a burst of the choroidal optic nerve. By using this model, we achieved the current issues which are faced by retinal illness.

III. MAIN CONTRIBUTIONS & OBJECTIVES

The main theme of this study is to identify the eye disease whether it contains an ulcer or not by using Machine Learning classification methods which are Support vector machine (SVM), Logistic regression, Naïve Bayes, and a Decision Tree to analyze leaf image data.

The execution plan is as follows.

A. Extraction of Data (Dataset)

B. Data preprocessing (Removing outliers, gray scaling of image, reduction of dimensions)

C. Model building

D. Implementation by ML algorithms

E. Comparing the models (Best accurate model)

IV. RELATED WORK

Cataracts, iridocyclitis, and corneal haze are all prevalent eye problems in the elderly. Using machine learning techniques, a computer-based smart system was created to categorize various eye illnesses. For each form of eye illness, characteristics are retrieved and employed by the classifiers, which include SVM, logistic regression, naive Bayes, and decision trees. Illness criteria are built for the fuzzy-based classifier. Additional guidelines for different illnesses may overlap and be difficult to distinguish from photographs.

To begin, characteristics are extracted from photographs of each illness and treated as symptoms. Expert rules are then built around these aspects. Finally, a decision tree classifier is created using forward chaining and depth-first search to complete the classification. According to the authors, this system is more thorough than previous equivalent systems. A graphical user interface had been created so that the program might be extensively utilized.

A reliable categorization method is needed for the early identification and prevention of glaucoma, a leading cause of blindness in the elderly. A data-driven technique is used instead of segmentation measures. Disease-independent changes such as lighting and size are eliminated during the pre-processing stage. Several characteristics are taken and integrated using pattern recognition to provide glaucomatous traits. The dataset had 1175 photos and a label excel sheets, and the success rate was 76%, which is equivalent to medical specialists. Understanding and theoretical study of the challenges in designing algorithms and learning theory have advanced. The review discusses current improvements in both supervised and unsupervised linear approaches as well as Bayesian networks in uncertain situations. These technologies have significantly improved illness detection and diagnosis in the clinical sector. There is relatively minimal pre-processing of the retinal pictures, but by utilizing SURF, points of interest and local descriptors are recovered for both normal and pathological images. The dataset included 672 non-DR pictures, 261 images with brilliant lesions, and 246 images with red lesions.

A visual dictionary is generated using a representative set of these descriptions. A feature vector describing the visual aspects of each picture is created using a technique called quantization. These feature vectors are then used to train a 2-class SVM classifier with a radial basis kernel to distinguish diabetic retinopathy from normal pictures. This cross-training paradigm is resistant to changes in retinal fundus color related to patient race.

A Machine Learning Engineer must spend time preprocessing or purifying data before constructing a model from scratch, and the vast majority of Machine Learning Engineers devote a significant amount of time and effort to this portion of their job. A few examples of data pre-processing techniques include outlier detection and treatment, missing value treatment, and the elimination of undesirable or noisy data, to name a few. It is necessary to undertake pre-processing for machine learning to be performed by medical guidelines. This includes data cleaning and normalization as well as noisy data filtering and the handling of missing values. It is vital to note that data pre-processing has a significant impact on the performance of machine-learning algorithms, and if it is not done correctly, it might result in biased output. The Weka knowledge analysis tool includes several different preprocessing and transformation methods to choose from. This technique is intended to make machine learning processes more resilient by identifying and eliminating unimportant features from the dataset to reduce dimensionality and enhance performance. Ignoring a minor symptom, on the other hand, could have catastrophic implications. Fortunately, standard taxonomies reduce redundant information, ensuring that no aspect is overlooked during the analysis and diagnosis process. Missing values might also harm machine learning. Specifically, two strategies were used in this study to deal with missing values: first, the deletion of records that had more than 60% of their values missing, and second, a two-step diagnostic method using segmentation.

V. PROPOSED FRAMEWORK

Data Preprocessing:

The eye disease dataset contains two parts where one consisting of images and another one consisting of labels. Here, the labels dataset is again divided into three parts which are category, type, and grade. The total images consisted of 712. Later, we resized to 100, 100 pixels in size

Splitting of Data:

To avoid overfitting, the dataset was divided into two categories: training datasets and testing datasets, which were divided by 80 percent and 20 percent, respectively.

Model Training:

In this project, we will use various ML algorithms to classify the disease and compare the performance of the model. Algorithms are,

- Logistic Regression
- SVM
- Decision Tree
- Naive Bayes

We have trained the model by using the above algorithms.

Prediction:

In classification, when we say "accuracy" we are usually referring to the degree to which something is accurate. It is one of the more visible metrics because it is the total number of cases that have been accurately detected.
The best model is identified by the highest value of accuracy.

Algorithms are discussed below:

***Logistic Regression**:*

Logistic regression only becomes a classification method when a decision threshold is included. The determination of the threshold value is a crucial component of Logistic regression and is reliant on the classification issue itself. The selection of the threshold value is heavily influenced by the accuracy and recall levels. Precision and recall should ideally both equal 1, but this is seldom the case. Low Precision/High Recall When minimizing the number of false negatives without necessarily reducing the number of false positives, we choose a decision value with a low Precision or a high Recall. In a cancer diagnostic application, for instance, we do not want afflicted patients to be classed as unaffected without careful consideration of whether the patient has been incorrectly diagnosed with cancer. This is because the lack of cancer may be recognized by other medical conditions, but the existence of cancer cannot be discovered in a candidate who has previously been rejected. High Precision/Low Recall When we wish to lower the number of false positives without necessarily decreasing the number of false negatives, we choose a decision value with a high Precision value and a low Recall value. For instance, if we are categorizing clients according to whether they would respond favorably or negatively to tailored advertising, we want to be certain that the customer will respond positively since a negative response might result in a loss of possible sales from the customer.

Support Vector Machine:

Support vector machines are a collection of supervised learning techniques used for classification, regression, and the identification of outliers. All of these are typical machine learning tasks. You may use them to identify malignant cells based on millions of photos or to anticipate future driving routes using a well-fitted regression model. There are specialized SVMs for specific machine learning issues, such as support vector regression (SVR), an extension of support vector classification (SVC). Keep in mind that these are just mathematical formulae optimized to get the most accurate response as rapidly as feasible. SVMs are distinct from other classification algorithms due to how they choose the decision boundary that optimizes the distance between the closest data points of all classes. SVMs establish a decision boundary known as the maximum margin classifier or maximum margin hyperplane. A straightforward linear SVM classifier creates a straight line between two classes. This implies that all the data points on one side of the line will represent one category, while all the data points on the other side will be assigned to a different category. This indicates that there are an endless number of lines from which to pick. The linear SVM method is superior to others, such as k-nearest neighbors since it selects the optimal line to categorize your data points. It selects the line that divides the data that is the furthest from the nearest data points.

Naive Bayes:

Naive Bayes classifiers are constructed using Bayesian classification techniques. Bayes' theorem is an equation that describes the connection between the conditional probabilities of statistical data. In Bayesian classification, the probability of a label given certain observed characteristics is P(L|features), which may be written as P(L|features). The theorem of Bayes gives us how to represent this in terms of quantities that are easier to calculate.

$$\frac{P(L_1 \mid \text{features})}{P(L_2 \mid \text{features})} = \frac{P(\text{features} \mid L_1)}{P(\text{features} \mid L_2)} \frac{P(L_1)}{P(L_2)}$$

Fig2. Formulae

Now we just need a model that can calculate P(features|Li) for each label. A model that defines the hypothetical random process that creates the data is known as a generative model. The most important aspect of training a Bayesian classifier is specifying this generative model for each label. The general version of such a training phase is a highly challenging process, but we can make it easier by making certain simplifying assumptions about the structure of this model.

Decision Tree:

The root of a decision tree is depicted at the top of an inverted decision tree. The black text in bold on the picture on the left denotes a condition/internal node depending on which the tree branches/split into edges. In this scenario, the decision/leaf is whether the passenger died or survived, indicated by red and green text, respectively, at the end of the branch that no longer splits. The simplicity of this technique is undeniable, although a real dataset would have many more attributes, and this is merely a branch on a much larger tree. The feature's significance is clear, and its relationships are discernible. This technique is more often known as learning a decision tree from data, and the tree seen above is known as a classification tree since its purpose is to categorize passengers as either surviving or perished. The only difference is that regression trees predict continuous quantities, such as the price of a home. Typically, Decision Tree methods are referred to as CART, which stands for Classification and Regression Trees

VI. DATA DESCRIPTION

The labels in this dataset are divided into three categories, five types, and five grades.

1. Category:

   corneal ulcers with a pointy appearance

   corneal ulcers with a point-flaky appearance

   corneal ulcers that are flaky

2. Types:

   type 0: No ulcer of the corneal epithelium

   type 1: Micro punctate

   type 2: Macro punctate

   type 3: Coalescent macro punctate

   type 4: Patch (>=1 mm)

3. Grade:

   Grade 0: No ulcer of the corneal epithelium

   Grade 1: Corneal ulcers affect only one quadrant of the cornea.

   Grade 2: Corneal ulcers affect two quadrants of the cornea.

   Grade 3: Corneal ulcers affect three or four quadrants around the eye.

   Grade 4: Corneal ulcers affect the cornea's central optical zone.

Fig3. Dataset Sample

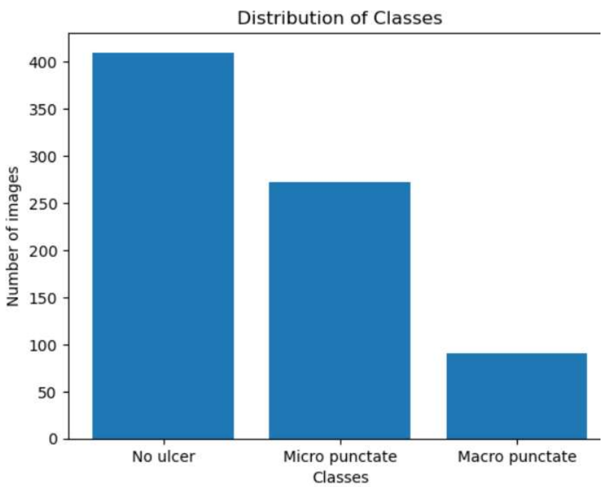

Fig4. Distribution of classes

VII. RESULTS & COMPARISION

Validation Method:

In classification When we say "accuracy," we are usually referring to the degree to which something is accurate. It is one of the more visible metrics because it is the total number of cases that have been accurately detected. When all the classes are equally essential, this is the most frequently encountered situation.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{(\text{True Positive} + \text{False Positive} + \text{True Negative} + \text{False Negative})}$$

Fig5.Formulae

Precision: It is implied as a measure of the proportion of successfully detected positive cases among all the expected positive instances. As a result, it is advantageous when the costs of False Positives are substantial.

Results:

After applying all the algorithms to the data set, we obtained varied accuracy percentages for different methods and conducted visualization for data when a forest fire occurred, depicting the region of fire that occurred now.

SVM:

```
Training data for SVC(probability=True)
Training completed
Prediction is done
Accuracy Score : 0.7597402597402597
Classification Report
              precision    recall  f1-score   support

           0       0.79      0.93      0.86        87
           1       0.69      0.72      0.71        50
           2       0.00      0.00      0.00        17

    accuracy                           0.76       154
   macro avg       0.50      0.55      0.52       154
weighted avg       0.67      0.76      0.71       154
```

Fig6.Result

Confusion Matrix:

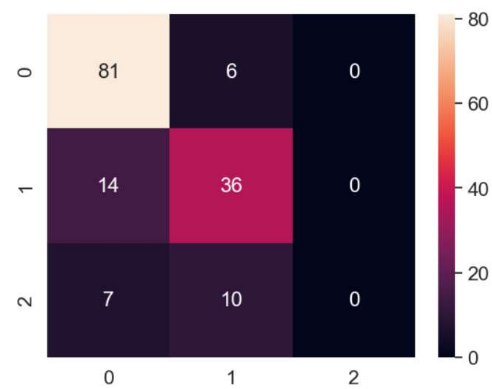

Fig7. Confusion matrix

Comparison between all the algorithms:

```
In [41]: plt.bar(x,y)
         plt.xlabel('ML Algorithms')
         plt.ylabel('Accuracy Score')
         plt.title('ML ALGORITHM COMPARISION')
         plt.show()
```

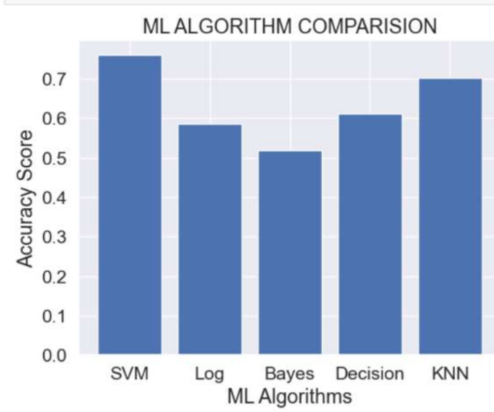

Fig8. Comparison

Conclusion and future work:

In this project, we used machine Learning methods for the classification of eye diseases. The primary goal of our approach is to detect the type of disease and classify it as healthy, moderate, or severe by training the images from the dataset and testing them. The fact that it applies the ML Method to the image results in it obtaining the probabilities of the image and providing the maximum probabilities, which aids in the feature extraction process.

As a result, it increases the accuracy of the trained and testing images while also assisting in the rapid detection of various types of eye diseases. The dataset has been used to train the model's parameters. The current approach shows signs of overfitting, which indicates that it is inefficient. The output of the SVM classifier is improved and validates and eliminates false positives. The technique that has been recommended has the highest overall accuracy (76 percent).

REFERENCES

1. A Multiscale Optimization Approach To Detect Exudates In The Macula Carla Agurto, Victor Murray, Honggang Yu, Jeffrey Wigdahl, Marios Pattichis, Sheila Nemeth, E. Simon Barriga, And Peter Soliz.
2. Tae-Young Heo, Kyoung Min Kim 1, Hyun Kyu Min, Sun Mi Gu, Jae Hyun Kim, Jaesuk Yun And Jung Kee Min "Development Of A Deep-Learning-Based Artificial Intelligence Tool For Differential Diagnosis Between Dry And Neovascular Age-Related Macular Degeneration ".
3. Chatterjee .B.M. Handbook Of Opthalmology, 6th Edition Revised And Enlarged, New Delhi, Cbs Publishers & Distributers, 2002.
4. R. S. Rekhi, A. Issac, M. K. Dutta, And C. M. Travieso, ''Automated Classification Of Exudates From Digital Fundus Images,'' In Proc. Int. Conf. Workshop Bio Inspired Intell. (Iwobi), Jul 2017, Pp. 1–6.
5. P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. Lecun, OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks, 2014.
6. D. Erhan, C. Szegedy, A. Toshev, D. Anguelov Scalable Object Detection using Deep Neural Networks Proceedings of the IEEE conference on computer vision and pattern recognition (2014), pp. 2147-2154
7. A. Kunwar, S. Magotra, And M. P. Sarathi, ``Detection Of High-Risk Macular Edema Using Texture Features And Classication Using Svm Classier," In Proc. Int. Conf. Adv. Comput., Commun. Inform. (Icacci), Aug. 2015, Pp. 22852289.1.
8. Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei.
9. ImageNet: A Large-Scale Hierarchical Image Database
10. D. S. Kermany, M. Goldbaum, W. Kai et al., "Identifying medical diagnoses and treatable diseases by image-based deep learning", Cell, Vol. 172, No. 5, pp. 1122-1131, 2018
11. Geoffrey E. Hinton, Simon Osindero, and Yee-Whye Teh. A fast learning algorithm for deep belief nets. Neural Computation, 18(7):1527–1554, July 2006.
12. Acharya, U. R., Kannathal, N., Ng, E. Y. K., Min, L. C., & Suri, J. S. (2006, August), Computer-based classification of eye diseases In Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE (pp. 6121-6124). IEEE.
13. Gardner, G. G., Keating, D., Williamson, T. H., & Elliott, A. T. (1996), Automatic detection of diabetic retinopathy using an artificial neural network: a screening tool British journal of Ophthalmology, 80(11), 940-944.
14. Winder, R. J., Morrow, P. J., McRitchie, I. N., Bailie, J. R., & Hart, P. M. (2009), Algorithms for digital image processing in diabetic retinopathy Computerized medical imaging and graphics, 33(8), 608-622.
15. Ibrahim, F., Ali, J. B., Jaais, A. F., & Taib, M. N. (2001), Expert system for early diagnosis of eye diseases infecting the Malaysian population In TENCON 2001. Proceedings of IEEE Region 10 International Conference on Electrical and Electronic Technology (Vol. 1, pp. 430-432). IEEE.
16. Bock, R., Meier, J., Michelson, G., Nyúl, L. G., & Hornegger, J. (2007, September), Classifying glaucoma with image-based features from fundus photographs In Joint Pattern Recognition Symposium (pp. 355-364). Springer, Berlin, Heidelberg.
17. Sajda, P. (2006), Machine learning for detection and diagnosis of disease Annu. Rev. Biomed. Eng., 8, 537-565.

[7] Jelinek, H. F., Rocha, A., Carvalho, T., Goldenstein, S., & Wainer, J. (2011, August) Machine learning and pattern classification in identification of indigenous retinal pathology In Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE (pp. 5951-5954). IEEE.

18. Wang, H., Hsu, W., Goh, K. G., & Lee, M. L. (2000). An effective approach to detect lesions in color retinal images . In Computer Vision and Pattern Recognition, 2000. Proceedings.
IEEE Conference on (Vol. 2, pp. 181-186). IEEE.
19. Patton, N., Aslam, T. M., MacGillivray, T., Deary, I. J.,

Dhillon, B., Eikelboom, R. H & Constable, I. J. (2006). Retinal image analysis: concepts, applications and potential . Progress in retinal and eye research, 25(1), 99-127.
20. Burlina, P. M., Joshi, N., Pekala, M., Pacheco, K. D., Freund, D. E., & Bressler, N. M. (2017). Automated grading of age-related macular degeneration from color fundus images using deep convolutional neural networks . JAMA ophthalmology, 135(11), 1170-1176.