National College of Ireland

An Approach to Classify Ocular diseases using Machine Learning and Deep Learning

MSc Research Project
Data Analytics

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MSc Project Submission Sheet

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An Approach to Classify Ocular diseases using Machine Learning and Deep Learning

Ankitha Mallikarjuna Gajaram
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Abstract

Ocular diseases are the global phenomena which can be seen across the globe. There are several eye diseases like Cataracts, Glaucoma, Diabetic Retinopathy etc., if neglected, or not diagnosed can lead to blindness or visual impairment. Many surveys conducted revealed poor society knowledge about the ocular disease and their drastic impact on an individual's life. Over the years, several government organizations as well as few NGOs came forward to spread awareness and educate people the importance of regular eye care routine and check-ups. On the other hand, to detect these diseases it consumes more time and requires to be done manually by highly qualified ophthalmologist. The aim of this research project is to develop a model that could help ophthalmologist in early detection of severe ocular diseases such as cataracts, glaucoma, diabetic retinopathy etc. Four different machine learning and deep learning models are applied, and model with high accuracy can be used to classify the eye disorders. Performance evaluation is done using accuracy score, precision, recall score, f1 score, loss, and accuracy graph. Accuracy score of Random Forest classifier, Support Vector Machine (SVM), k – Nearest Neighbor and Convolution Neural Network is 52%, 59%, 61% and 68% respectively.

Index terms: *Convolution neural network, ocular, cataracts, deep learning, machine learning, glaucoma.*

1 Introduction

Blindness and Vision Impairment have always been a global issue across the world. According to many surveys, the majority of population consider eye care as a minor concern. Several studies have put forth the importance of eye care and vision, as well as its direct consequences with various aspects of life which includes individual's health, sustainability growth, economy etc. Many eye diseases such as glaucoma, diabetic retinopathy, cataracts are the leading and severe cause of blindness and vision impairment. There are some eye diseases like Age related macular degeneration which affects the vision of aged people, but the major concern is some of these diseases tends to be developing in newborn infants and due to lack of technology it cannot be detected at the earlier stages which causes in visual impairment. World Health Organization in their studies of eye health have reported that, over millions of people are suffering with blindness as these high-quality surgeries are not affordable. (Burton et al., 2021) committee emphasized on the significance of eye health as well as put forth the evidence demonstrating impact of improvement in eye care health sector which will help an individual to reach their sustainable goals can help in reducing the poverty and while increasing the productivity. The main concern with these diseases is the amount of time it takes to show symptoms is longer which makes it very important to be examined by the optometrist on the regular basis.

The research is conducted by procuring the fundus images of the eye on which machine learning and deep learning methods can be implemented to detect various ocular diseases like glaucoma, cataract, diabetic retinopathy etc. This study can help ophthalmologist to detect eye disease quickly and prescribe the patient with appropriate diagnosis or immediate surgery if required. Early detection of ocular disease helps in preventing blindness and vision impairment. This project could help in making the detection process faster as well as it will eliminate consulting qualified optometry saving lot of time, who can be further consulted only for critical cases or high-quality surgeries.

According to the statistics conducted for 'the lancet global health commission' in year 2020, 1.1 billion of the population was suffering from distant visual impairment. Out of which majority of the population live in low and middle-income countries where high quality eye care services are lacking. If appropriate measures are not taken, then by year 2050 the count of distance visual impairment are expected to increase to 1.8 billion. Not only distant visual impairment, other sever eye diseases causing vision impairment are cataract, glaucoma, and uncorrected refractive error. If the requirements for early detection and treatment of these diseases are successfully met than, it might increase the sustainability goals of individual or may increase the work productivity or economy.

Motivation behind this research is to try and develop a machine learning model which helps in early detection and classification of several eye disease, that ultimately can provide high-quality assistance to ophthalmologist as well as helping millions of populations from blindness and vision impairment. This work can further be used on the larger scale health sector for disease diagnosis which will help individual to fulfil their life goal, further impacts directly and indirectly to the progress of the nation, nation's economy.

1.1 Research Question:

Many people can avoid vision loss if severe diseases like glaucoma, cataract can be detected and diagnosed, if these diseases are detected early. Classifying and predicting the ocular diseases ahead of time with the help of Artificial Intelligence or Machine Learning techniques can assist an ophthalmologist recommend preventive methods and if required prescribe clinical treatments to avert blindness.

Research Question: *"How precisely can a machine learning and deep learning models can help in detecting and classifying the ocular diseases using fundus images of the human eyes?"*

1.2 Format of the paper:

The format of the paper has been organized as per the required standards and explained further for simple understanding of the paper. Next comes the Section 2 – 'Literature Review', that provides the work which has been carried out previously in the relevant field. Section 3 – 'Methodology' gives general overview of the methods to be applied throughout the research project. Section 4 - 'Implementation' gives brief information about all the model applied in the project. Section 5 - 'Evaluation Results', results are demonstrated and explained properly. Section 6 - 'Discussion and Conclusion' and Section 7 - 'Future work'

2 Related Work

Machine Learning has always been capable of providing tremendous state-of-art results in many health sectors issues. Out of which ophthalmology is an upcoming field advancing from Artificial Intelligence and Machine Learning. First machine learning method applied in the field of medical science was in 1970's and from that era the machine learning has proven its capacity in assisting, screening, and diagnosing of several diseases (Armstrong and Lorch, 2020). Many of the Artificial Intelligence techniques have been applied till date to help optometrist for diagnosis or for screening of eye diseases like keratoconus, age-related macular degeneration (AMD), retinopathy of prematurity (ROP) etc. Similarly in following paper, Caixinha & Nunes (2017) aims on discussing the major contribution of machine learning algorithms for monitoring and diagnosing diseases when it comes to the context of vision science. Also, researchers (Caixinha and Nunes, 2017) emphasizes on how many of the eye diseases can be prevented from happening if they are detected on its earlier stage. Further the importance of best approach to apply machine learning techniques was discussed in the same research paper. To achieve good and desirable results from machine learning models it is very important that all the possible bias should be kept minimal or should be tried removing. Although in many cases the performance and the output of the machine learning process depends on the dataset given as input.

Many articles and research have made more use of supervised machine learning techniques in clinical applications when compared to unsupervised machine learning methods. Out of classifiers are universally used which helps in classifying images if they are diseased eye or non-diseased eye, the images are called the fundus image which is basically the photograph of eye retina from inside that helps in validating the presence of any sort of disorder in the eye.

These fundus images have now become the most important part of clinical references as they help in examine the disease as well demonstrates the severity and type of eye disease an individual is suffering. (Song et al., 2019) in the research performed semi-supervised machine learning method by first extracting features from the fundus images of the eye like texture, wavelet and sketch and then applied the classifier method on the images, causing to prevent the problem of overfitting.

Literature survey provides tons of meaning information about the research background, when previous work was conducted on which is the most severe ocular disease, the studies has shown that out of all diseases, cataract is the most severe disease and half of the blindness and visual impairment are caused due to cataracts. (Qiao et al., 2017) described how cataracts are drastically causing blindness across the globe and how the fundus images are the key to detect and diagnose cataract. In the research the fundus images were divided equally into 17 images for feature extraction, and once the extraction process was done, the feature vectors were compared to the genetic algorithm and super vector machine was implemented to classify the images which gave 87.52% of accuracy.

It has been seen that for quicker detection and further diagnosis, medical health sectors have been relying on artificial Intelligence (Malik et al., 2019). Further they emphasize on how important it is to have reliable, accurate data, so that the machine learning techniques when performed can provide desired and meaningful results. In the research, procured the standard format of the data which included all the patience details, this information was carefully stored by medical experts. On the same data, authors applied machine learning algorithms like Random Forest, Artificial Neutral Network, Navies Bayes, Decision Tree, out of which decision tree method performed better and provided accuracy when compared with others.

There are many aspects to be considered and controlled, many changes in our body or lack of vitamins, proteins can also lead us to eye disorder. In case of Diabetic Retinopathy, people suffering from diabetics are more intend of suffering Diabetic Retinopathy. It usually develops when the suggested amount of blood sugar level is not in control for a very long period of time. (Seetah et al., 2021) implemented a Convolutional Neural Network methodology which takes input as a colored fundus image of human eye retina and further gave an accuracy of 84 percentage. Seetah et al., (2021) in the paper discusses the importance of such models in the health sector for quick detection and diagnosis of the disorder, further stating the improvement of their model's specificity and sensitivity which where 98.25 and 92 percentage respectively. There are four stages of diabetic retinopathy, they are mild nonproliferative diabetic retinopathy (NPDR), moderate NPDR, severe NPDR, proliferative diabetic retinopathy. It becomes very difficult as well as time consuming to complete the procedure of manually detecting the different type of eye disorder. It has been very crucial to find the system that can automate the process of diagnosing the disease.

New techniques and methodologies should be developed as there has been need of early detection of eye disorders to prevent blindness. In case of diabetic retinopathy disorder, even early disclosure of diabetes can be helpful for an individual, so that he/she can examine their actions, change it, and save themselves from severe visual impairment (Chetoui et al., 2018). They proposed a system that uses Local Ternary Pattern (LTP) and Local energy-based shape histogram (LESH), in contrast to the Local Binary Pattern (LBP) and wavelets that were mostly commonly used in past studies for feature extraction. The reason behind selecting these techniques is that they are good at capturing pixels irrespective of contrast, color, or noise present in the images. Further to distinguish diabetic retinopathy and normal eye images

support vector machine was used, out of which LESH had the higher accuracy of 90 percent using Radial Basic Function (RBF) kernels.

(Kononenko, 2001) in the study illustrated all the crucial and necessary information by performing proper analysis on the data from the past history and further providing the trends which can be seen in the future by analyzing two case studies. Kononenko, (2001) emphasized on naïve Bayesian classifier and show cased its significance in the past by listing out few examples, further explaining how in historic time simple machine learning techniques were used for medical purpose. In the upcoming years it is evident that machine learning techniques will play a crucial role in performing analysis of medical data and will considerably help medical experts in diagnosing the patients. Some studies have solely research on certain eye diseases like glaucoma which is discussed further.

Glaucoma is an eye disorder causes when there is damage to the optical nerve. Most of the population in Japan are suffering from glaucoma as well as it is one of the leading causes of blindness. (An et al., 2018) research focuses on applying classification machine learning techniques on the data and before randomly splitting the image data for training and testing, they were divided into four different types of optic disc. All the image data was acquired using optical coherence tomography, on which machine learning classifiers like neural network, naïve bayes, SVM were applied. There were in total 36 parameters which were extracted. When the comparison of the models was illustrated neural network was the one with the outstanding performance whose accuracy rate was 87.8 percentage that too considering only nine parameters.

Similarly, in paper (Treigys & Šaltenis, 2007) neural network classifier method with one hidden layer was implemented. In data preprocessing section use of principle component analysis (PCA) was used to reduce total number of features, that is from 27 to 10. Satisfying output results were accomplished because of implementing network activation function logsig as well as due to implementing Levenberg-Marquardt algorithm. Not only all the neural network methods, but some research has also made use of Fuzzy rule-based system which is well-known in providing exceptional results while handling complicated nonlinear relationship. This rule-based system works on the predefined set of rules and strategies which are fed via expert in the field. The system uses dataset which is entered by medical experts and patients in the form like data entry, using which the output will be given as the name of the disease. The system is trained and tested with the data of all the disease symptoms entered by medical expert and physicians then the fuzzy rule set and will further create the weights to make the informed decision. The system is designed to support the medical experts which will assist them to detect disease and to provide proper diagnosis at the correct time to prevent from visual impairment or blindness (Agrawal et al., 2015).

(Burgansky-Eliash et al., 2005) defines classifiers of machine learning technique as a trained automated computerized system that has the unique ability to understand the relation between multiple parameter which are given as input further providing the diagnosis detected using those parameters. Researcher in the paper proposes a system as a unique solution which helps in investigating if or not the machine learning classifiers can effectively detect the glaucoma eye disorder using the data of optical coherence tomography. With the implementation of support vector machine using 8 parameters the proposed system for glaucoma detection have achieved 0.981 of accuracy, for classification of early detection of glaucoma and advanced detection of glaucoma the system achieved 0.854 of accuracy that with the help of utilizing three parameters only. Thus, concluding in the paper that with the help of automated machine

learning techniques can be utilized for detecting eye disorders like glaucoma with OCT data. On the other hand, (Ing. JAN ODSTRČILÍK, 2014) in the paper illustrates the advantages of Fundus camera device and how fast and cheaper these images are which can be used to examine human eye's retina. Not only them but many research have been carried out to develop computer aided system based on the fundus images. Overall Ing. JAN ODSTRČILÍK (2014) proposed two methods with a thought of contributing to the field of retina image processing, one of this methodology is segmentation of blood vessel and another one is assessing of retinal nerve fiber layer (RNFL) in the fundus images with the high-resolution color.

Blindness and Visual impairment are the serious issue across the globe, to prevent them it is advised to conduct a regular eye check up as much as possible. Even though severity of this issue is worldwide, India is the first country who took initiative of spreading awareness and conducting blindness control programs. Many articles have showcased the insufficiency of optometry, inadequate resources for curing huge population going through several ocular disorder (de Souza et al., 2012). In the list of eye disorders, cataracts are the most seen ocular disease in majority of the population, many medical experts are trying hard to bring advancement in the surgical and detection techniques of cataracts and due to new technologically discoveries faster recovery in the patient's retina can be seen (Liu et al., 2017).

3 Research Methodology

Knowledge Discovery in Database (KDD) and CRoss Industry Standard Process for Data Mining (CRISP-DM) are the two most commonly used research methodologies when it comes to data mining project. Basically, these methodologies are useful to illustrate life cycle of a particular project. Both the methodologies include different steps to be carried out while working on a project. The current research study uses CRISP-DM to carry out the whole project. (Chapman et al., 2000) this is a simple a descriptive stage, where that the beginning of the process it's quite not possible as well as difficult to find all the relationship within the data. It is important to understand that the tasks/phases of the life cycle could have a relationship which is further totally dependent on goals, research background or on the data. There are in total six different stages in CRISP-DM, which are illustrated in the figure 1 below.

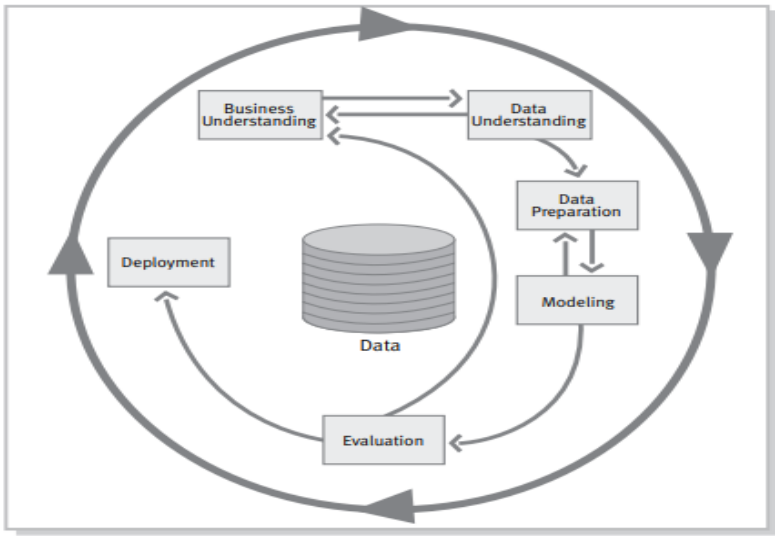


Figure 1: Stages in CRISP-DM

3.1 Business Understanding

Business Understanding is the first step in CRISP-DM methodology, where the main intend of the research project is to understand the overall requirements of the problem in the research. Eye disorder are the leading cause of blindness and vision impairment. Detecting severe ocular diseases such as cataract, diabetic retinopathy, glaucoma at the early stage can prevent visual impairment and the ophthalmologist can provide preventive measures for the same before it's too late. Usually these develop at a very slow pace and symptoms can be seen at the later stages. Manually following all the procedures and tests for diagnosis is very time consuming. Optometry could benefit if automated computer system can detect and classify the disorder. Therefore, machine learning models like Support Vector Machine is implemented using fundus images of human eye retina to classify the eye disorder.

3.2 Data Understanding

It is the next phase in CRISP_DM methodology, where data is initially collected, and further proceeding with understanding brief and meaningful insights of the data. For this research project the dataset is procured from the open-source platform called Kaggle. This dataset comprises of several fundus images of human eye, the fundus images are divided into four parts normal fundus, cataract fundus, glaucoma fundus, diabetic retinopathy fundus images and then stored separately into different folders. The images are taken using fundus camera which is a microscope mainly used to inspect structure of retina, eye lens, optic cup, optic disc etc. Dataset includes a total amount of 600 high quality JPG fundus images. The height and width of the fundus image is 2464x1632 and 3 is its dimension of color RGB. Link of the dataset is https://www.kaggle.com/jr2ngb/cataractdataset.

3.3 Data Preparation

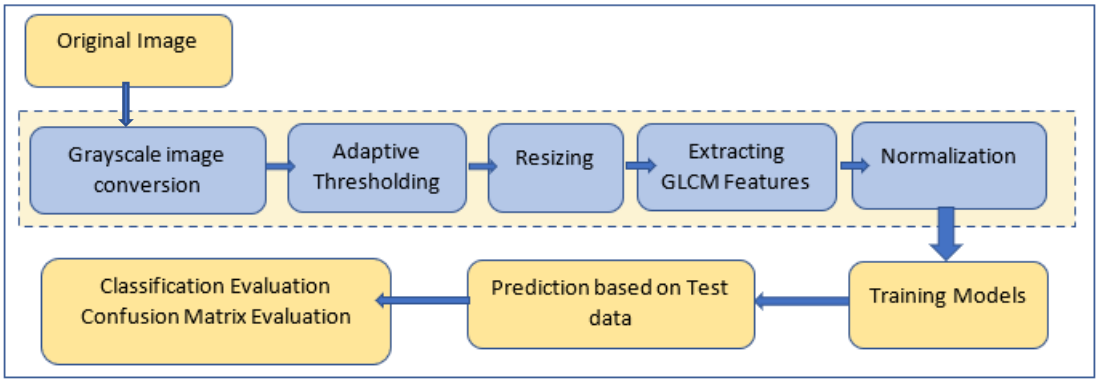


Figure 2: Image Preprocessing & Project Flow

It is an important phase were all the data cleaning, selection, transformation of the data is carried out, in order to feed the machine learning models, all the task carried out in this stage affects the results of the modelling techniques. The image with large dimensions takes time to process it and it may result in loss of computational cost. So, to reduce the computational cost we need to remove the unwanted Region of Interest (ROI) from our image. In order to acquire, the required ROI initially we need to start converting all the images into Grayscale. Once the

conversion of image is achieved, the image is further transformed into threshold image (as known as Binary Image). The reason behind this transformation is to make the image machine readable for further processing. All the images have unwanted black background, which as a part of data cleaning is removed. So, the ROI can be procured for further analysis.

3.3.1 Feature Extraction

In this project, the feature extraction process is carried out using Grey Level Cooccurrence Matrix (GLCM) tool. GLCM is the most commonly used feature extraction tool, it is basically a matrix that depicts how frequently a number of different sets of pixels exist in grey level image. The calculation of the GLCM matrix is carried out only on certain set of distance and angle (Alazawi et al., 2019). Among fourteen Haralick's feature, four features, Contrast, Entropy, Homogeneity and Energy are used in this research project. The definition of these four features is give below:

1) Contrast: This statistical feature of GLCM is used to measure the images local contrast.

$$Contrast\ (d,\theta) = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i-j)^2\ P_d^{\theta}(i,j)$$

where from P(i,j) image, (i,j) are the elements obtained in GLCM(unnormalized), N depicts the total count of gray-levels and $P^{\theta}{}_d$ demonstrates the pixel probability at Θ direction with d interval.

2) Correlation: Indicates the correlation relationship of any two pixels available in a considered pixel pair.

$$Correlation = \sum_i^M \sum_j^N \frac{(i-\mu)(j-\mu)P[i,j]}{\sigma^2}$$

where μ is mean and σ is standard deviation of the P(i,j) image.

3) Homogeneity: This feature measures local pixel pairs homogeneity and the homogeneity will be greater if each pixel pair's gray level are found to be similar.

$$Homogeneity = \sum_i^M \sum_j^N \frac{P[i,j]}{1+|i-j|}$$

4) Energy: The feature aims at counting the total number of repeated pixel pairs, if the energy is high then chances of occurring of one pixel pair many a times is the possibility.

$$Energy(Angular\ Second\ Moment) = \sum_i^M \sum_j^N P^2\ [i,j]$$

In equation 2, 3, and 4, M & N represents dimensionality of P[i,j] image.

3.3.2 Feature Scaling

Feature scaling plays a crucial role in preprocessing of the data. The implementation of this step is necessary because if it is not done then there will be a huge imbalance in the output results, for example the greater value in a range of data will be considered as the highest value and the smaller value in a range will be the lowest value. There are two techniques of feature scaling which are most commonly used, they are Normalization and Standardization. Normalization technique is applied to the data when we require our value to range between 2 number, that could be [0,1],[-1,1]. We can apply standardization method when we need our data to have mean = 0 and variance = 1, which helps in making a data unitless. In this research project, I have used Min Max Scaler for performing feature scaling and have given the range between 0 and 1.
Formula for Min Max Scalar is given below:

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

3.4 Modeling

3.4.1 Random Forest Classifier:

Random Forest Classifier is the machine learning technique that is developed on the concept of multiple decision trees. Random Forest Classifier is a Supervised machine learning classification technique, it depends on several self-learning decision trees which are also known as forest. The purpose of utilizing many different decisions tree is that many self-learner trees combined together will make a robust and strong decision which might not be able to achieve with single decision tree. The decision trees used by the random forest automatically set out the rules at each point of their nodes depending on the train dataset. All the decision tree used in the classifier is randomized, hence the name random. All the decision tree in the random forest executes parallelly as well as while constructing the decision tree no interaction happens between them. Random Forest comes under bagging technique. Below figure shows the overall structure of the Random Forest.

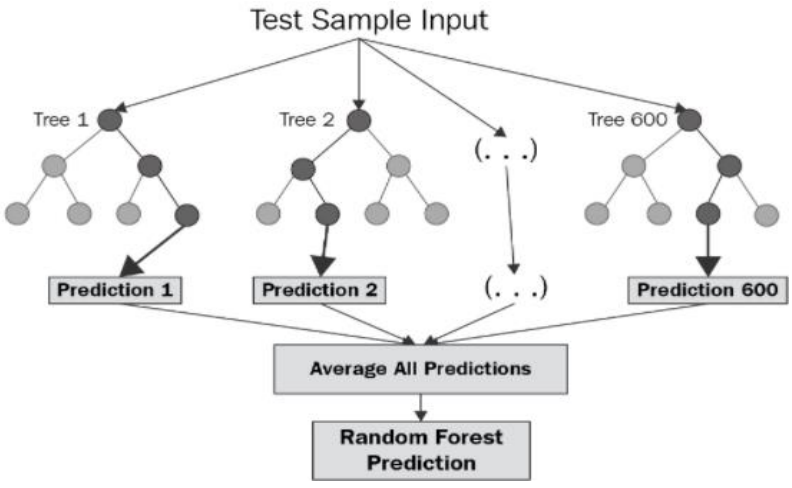


Figure 3: Architecture of Random Forest Classifier

A Random Forest when executes, combines, and aggregates the output result of all the predictions and provides the accuracy. (Chowdhury et al., 2019) used Random Forest Classifier as an approach to detect the abnormalities that tends to happen by diabetic retinopathy and age-related macular degeneration. Due to its merits, Random Forest is used to achieve better classification result.

3.4.2 K-Nearest Neighbors Classifier (K-NN)

K-Nearest Neighbors is the supervised learning classification technique in which the algorithm collects all the sample cases and if a new case comes, it classifies the case based on the majority samples of the nearest neighbors. K-Nearest Neighbors is well used to classify unlabeled data and put them in different containers of same sample. Whenever a new item comes, the distance between the nearest neighbor is calculated to place them into different containers and classify them. The distance is calculated using the Euclidean distance which is the nearest distance between two points. KNN stores all the dataset passed to it and later performs the classification action to the dataset. The value of k determines the level of classification, higher value of k results more accurate results as the resultant variance will be low.

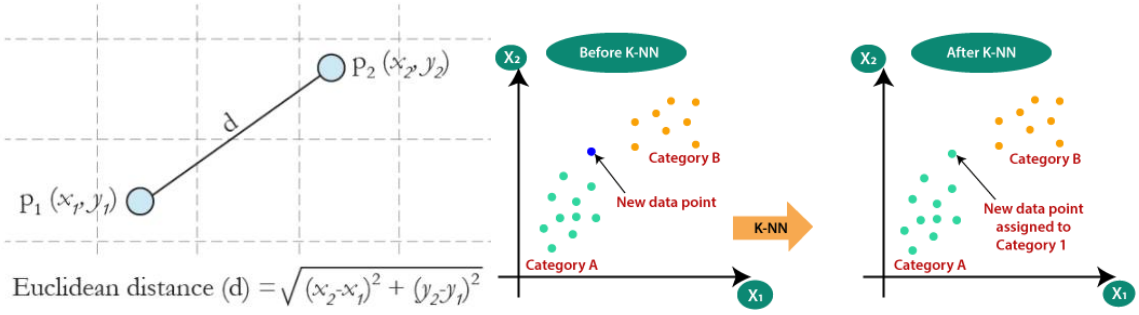


Figure 4: k-Nearest Neighbor

3.4.3 Support Vector Machine (SVM)

Support Vector Machine is a supervised machine learning method that is widely used for classification problems and for regression problem. Sometimes it is also used to detect outliers in the data. SVM method draws the decision boundary that divides dimensionality space into the set of a class due to which we can enter the new data point for future references. The line or the decision boundary that divides the data points is known as Hyperplane. With the help of the data points (or also called as vectors) it becomes easier to create hyperplane. These extreme points that creates the best line or the hyperplane are known as support vectors and overall, the algorithm is called as support vector machine. Most of the pattern classification project as well as image classification research uses SVM for better outcome. Using Least Square Support Vector Machine (LS-SVM), Polat & Güneş (2007) have developed a Breast Cancer diagnosis system, analyzed all the important factors like sensitivity, specificity, confusion matrix and procured the higher accuracy percentage of 98.53. By the past literature survey, it can be observed that the SVM would be the best fit to image classification problems, due to its merits and promising outcomes we, in this research paper have used SVM for classifying different eye disorder.

3.4.4 Convolutional Neural Network (CNN)

To understand CNN first we need to understand what neural network are and what they mean in the area of machine learning and deep learning. Neural Networks consist of single nodes that further fashions into different layers in a network. We can say that the neural networks are constructed/shaped just like our brain, where several neurons are connected to different regions of our brains. Similarly, a CNN is a type of neural network, with the difference of multiple layers in it. CNN is also known as ConvNet which is vastly used in classification process. ConvNet includes distinct number of layers like Convolution, Max pooling layer, flatten, activation layer and fully connected layer, that can be adopted to implement on discrete application. While performing image processing heuristics creates filters which helps CNN to understand the useful characteristics of the input image. There are three different kinds of CNNs, they are 1D, 2D, 3D CNN. When the research application includes image data then most commonly 2D CNNs are used. Below shown is the block diagram of ConvNet.

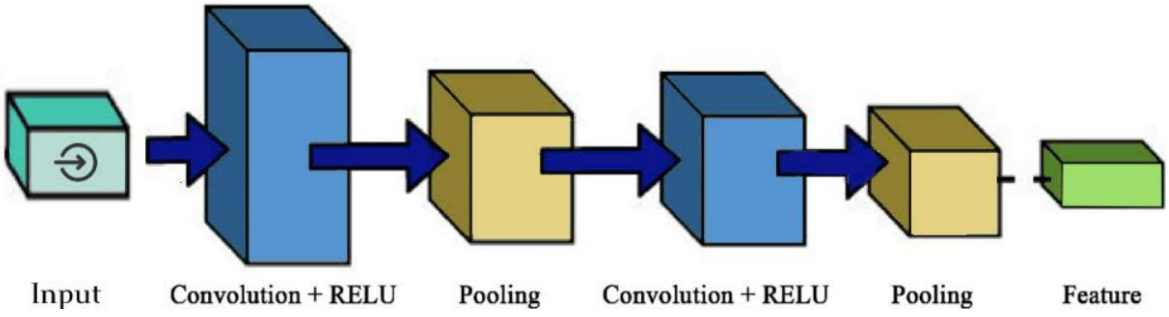


Figure 5: CNN Architecture

(Abbas, 2017) developed a computer aided system to diagnosis the glaucoma disorder using CNN machine learning technique using softmax linear classifier and 99 percent accuracy was achieved. Similarly, (Juneja et al., 2020) implemented an automated glaucoma detection system using CNN, fifty fundus images were used to test the model and achieved accuracy for disc as 95.8 percent and cup segmentation as 93 percent. Due to its wide application and higher accuracy rate, in this research project ConvNet to classify the different eye disorders.

4 Implementation

Different machine learning models have been implemented for classification of ocular disease. The machine learning techniques applied to classify eye disorders are CNN, SVM, Random Forest and KNN. Previous literature survey results are more inclined to these models, for better accuracy and also sensitivity and specificity results are examined for better outcome. The image file used for classification of ocular diseases includes four categories of images, they are normal eye, cataract eye, glaucoma eye, diabetic retinopathy.

4.1 Implementation of Random Forest Classifier, K-NN and SVM

- Initially loading process of the image data to the OpenCV method is carried out. The OpenCV method by default loads the image in BGR (Blue, Green, Red) format, but we need the images in RGB format, so to achieve this cvtColor() method is used.
- Next step after color conversion is to prepare the data for feature extraction. To carry out feature extraction, we need image data to be in Grayscale because it has only one dimension.
- When all the images are obtained in Grayscale (which ranges from 0-255), the next task to use those image data and then convert them into threshold images for proper segmentation of the image. Thresholding is quite a straightforward method, its purpose is to create Binary image of the grayscale image, which helps machine to understand the foreground and background. A pixel of the image is considered as background pixel, if its value is less then the threshold, else the pixel is set to be foreground pixel.
- The images procured in this research project were variable in size, which were inconsistent as well some images were too large for processing. Hence, the resizing of the original images is carried out. Further feature extraction using GLCM is accomplished where the four statistical features are selected for further classification. And then data normalization is performed. The normalized data is then segregated into training data and testing data, after which the image data is completely ready for applying machine learning techniques.

4.1.1 Random Forest Classifier

Once all the preprocessing steps are successfully accomplished, then the data is all set to implement the model. To find the best parameter for random forest classifier, we use Hyperparameter tuning. In this method, the parameters are needed to be user defined and are applied before learning process (Figure 6). It is mainly used to find the best possible parameter among the other mentioned parameters. Here GridSearchCV function is used to iterate over the predefined value and provides the best value from the other hyperparameters (Figure 6).

```
from sklearn.model_selection import GridSearchCV

parameters = {'n_estimators': [5,10,20,40,90]}
random_forest = RandomForestClassifier()
clf = GridSearchCV(random_forest, parameters)
clf.fit(x, y)
sorted(clf.cv_results_.keys())
print(f"Random Forest Classifier Best paramaters {clf.best_params_}")
print(f"Random Forest Classifier Model score {clf.best_score_}")
```

```
Random Forest Classifier Best paramaters {'n_estimators': 90}
```

Figure 6: Parameter Evaluation

Now, since the hyperparameter process using GridSearchCV function is completed on training data, we can now proceed further and carry out prediction process on test dataset. Below Figure 7 shows prediction on test data.

```
#prediction on the test data
y_predicted = model2.predict(x_test)
y_predicted
```

Figure 7: Random Forest Classifier test data prediction

4.1.2 K-NN

After normalizing data, which is an important step, the data is split into train and test. While implementing K-NN, again we use GridSearchCV, just like we did for random forest, to find the optimal parameter value for k (Figure 8), which helps to decide in which class the image belongs to. The k value is calculated by the Euclidean distance which in turn decides the class of the image. K-NN is the simplest yet good classification model due to its low tolerance to the noise if present in the data.

```
from sklearn.model_selection import GridSearchCV

parameters = {'n_neighbors': [7,9,13,17]}
KNN = KNeighborsClassifier()
clf = GridSearchCV(KNN, parameters)
clf.fit(x, y)
sorted(clf.cv_results_.keys())
print(f"KNN Best paramaters {clf.best_params_}")
print(f"K-Nearest Neighbors Classifier Model score {clf.best_score_}")
```

```
KNN Best paramaters {'n_neighbors': 17}
```

Figure 8: Optimal Parameter Search

After the selection of the best ‘k’ value, prediction on test dataset is completed, and the below Figure 9 depicts the same.

```
#prediction on the test data for KNN
y_predicted = model3.predict(x_test)
y_predicted
```

Figure 9: k-NN test data prediction

4.1.3 SVM

SVM uses sklearn python package, we have used this package to so that we can uses its feature like kernel function, which includes Radial Basis Function (RBF), linear, non-linear, sigmoid, polynomial (Figure 10). The task of the function is to accept data as input and then transforming that data into the format required for further processing. From sklearn package the function svm.SVC() is used to execute SVM model and then predict() function is used on test data (Figure 11).

```
from sklearn.model_selection import GridSearchCV

parameters = {'kernel':['rbf','linear','poly','sigmoid'], 'C':[5,15,30,50]}
svc = svm.SVC()
clf = GridSearchCV(svc, parameters)
clf.fit(x, y)
sorted(clf.cv_results_.keys())
print(f"SVM Best paramaters {clf.best_params_}")
print(f"SVM Model score {clf.best_score_}")
```

```
SVM Best paramaters {'C': 15, 'kernel': 'poly'}
```

Figure 10: kernel selection for SVM

```
#prediction on the test data for SVM
y_predicted = model.predict(x_test)
y_predicted
```

Figure 11: test data prediction of SVM

4.1.4 CNN

CNN is a feed-forward like architecture which can get the image and learn it with learnable weights. In the project, while building the CNN model, we used sequential type model. This allows us to apply other layers to the model with help of 'add()' function. The first layer applied in the model was the convolution layer, we have used two convolution layers. After convolution layer, activation layer is added. Out of the four activation layers, three layers have activation function called rectified linear function (relu), and for the fourth activation layer softmax function is applied. Then there is BatchNormalization, which is useful as to avoid overfitting and helps to normalize previous layers output. MaxPooling layer is implemented so reduce and summarize the features that are produced in the convolution layer. Flattened layer plays an important role in the CNN, as it is useful to make a connection in between Convolution layer and Dense layer. Next is the Dense Layer applied in the model, it is basically a neural network that takes output of all the other layers(i.e., previous) as an input.

5 Evaluation Results

A brief description and results of the data pre-processing carried out is shown in this section, before in depth discussing about evaluation and results of different models implemented. Initially the image data is imported into python code and then all RBG images are converted in Grayscale. Once the Grayscale image is obtained using adaptive thresholding the image are set to be in a particular range between 0 and 1, and then to get the region of interest, the images have been cropped and further resized all the image data to 400x400 as in Figure 12 shown below.

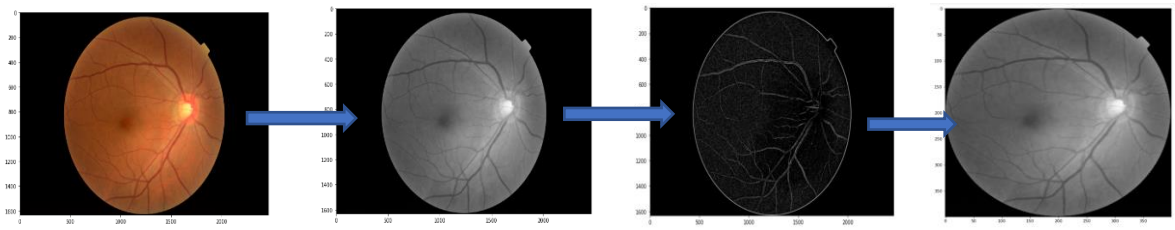
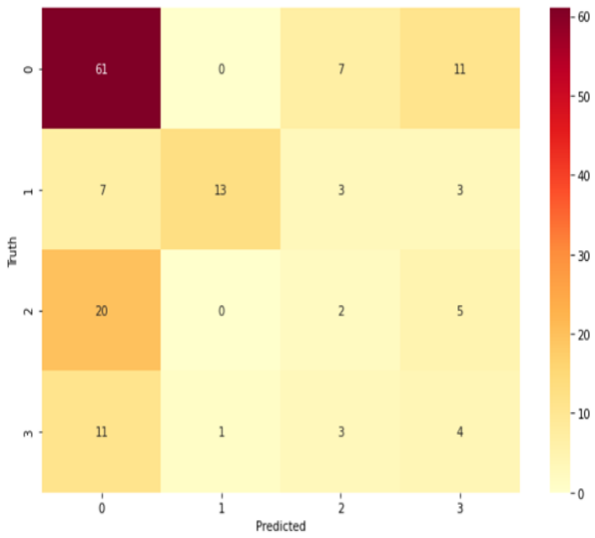


Figure 12: Fundus image processing

5.1 Random Forest Classifier, SVM, k-NN

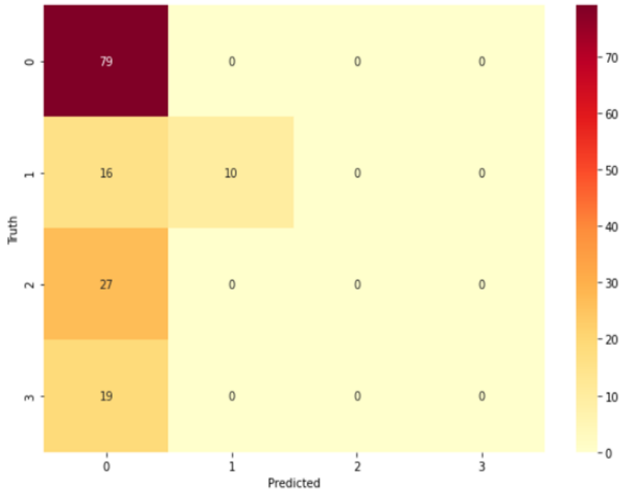
A thorough execution and analysis of the machine learning techniques applied to classify ocular disorder is evaluated in this part of the section. In this research project, we have used Accuracy score, Confusion matrix, precision, recall score, f1 score, Accuracy Vs Epoch graph, Validation Accuracy Vs Epoch, Loss and Validation Loss per epoch graph for performance evaluation of the models implemented. Below Figure 13, Figure 14, Figure 15 shows the confusion matrix and classification report of random forest, SVM, and k-NN model respectively. The confusion matrix depicted in figure 13,14,15 provides the useful information like, on how many images the matrix results are gained and how accurately the actual values and predicted values have been predicted correctly for each of the class. Also the below Figure 13,14,15 illustrates classification report, which includes precision, recall, f1 score of the same models. In Figure 13, when we take a look at the classification report for class 0, we can see the that the precision value is 0.62, recall is 0.77, f1-score is 0.69 and support i.e the number of test images considered is 79. Similarly, we can observe precision, recall, f1-score, and support values of different classes from the classification report.

Performance Evaluation



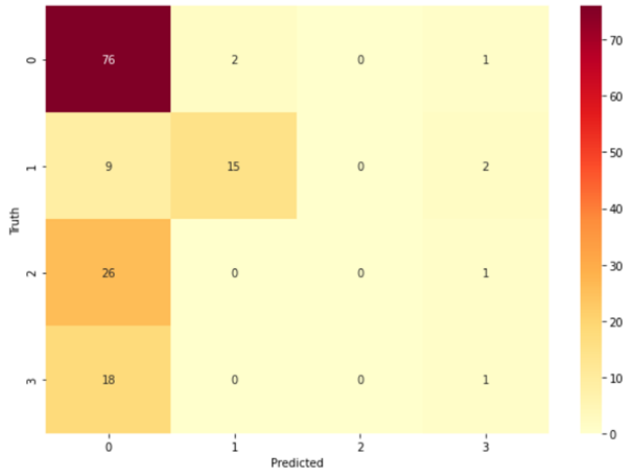
	precision	recall	f1-score	support
0.0	0.62	0.77	0.69	79
1.0	0.75	0.46	0.57	26
2.0	0.13	0.07	0.10	27
3.0	0.19	0.21	0.20	19
accuracy			0.52	151
macro avg	0.42	0.38	0.39	151
weighted avg	0.50	0.52	0.50	151

Figure 13: Random Forest Confusion Matrix and Classification Report



	precision	recall	f1-score	support
0.0	0.56	1.00	0.72	79
1.0	1.00	0.38	0.56	26
2.0	0.00	0.00	0.00	27
3.0	0.00	0.00	0.00	19
accuracy			0.59	151
macro avg	0.39	0.35	0.32	151
weighted avg	0.47	0.59	0.47	151

Figure 14: SVM Confusion Matrix and Classification Report



	precision	recall	f1-score	support
0.0	0.59	0.96	0.73	79
1.0	0.88	0.58	0.70	26
2.0	0.00	0.00	0.00	27
3.0	0.20	0.05	0.08	19
accuracy			0.61	151
macro avg	0.42	0.40	0.38	151
weighted avg	0.49	0.61	0.51	151

Figure 15: KNN Confusion Matrix and Classification Report

5.2 CNN

While applying CNN model, we have implemented two CNN models on the image data. The reason behind this is demonstrate if there's any changes to the accuracy score is seen when changes in the activation layers are made like changing from relu to softmax. Below figure of graphs illustrated are of CNN. Figure 16(a) and Figure 16(b) graph depicts Val Accuracy and Val Loss for 40 epochs. It is seen in the graph that there's no major over-fitting issue, after few epochs we can see in the graph, that the model's accuracy is increasing gradually and on the other hand a decrease in the graph can be seen for Val loss. Accuracy score of CNN Model obtained is 68 percent.

Loss and Accuracy

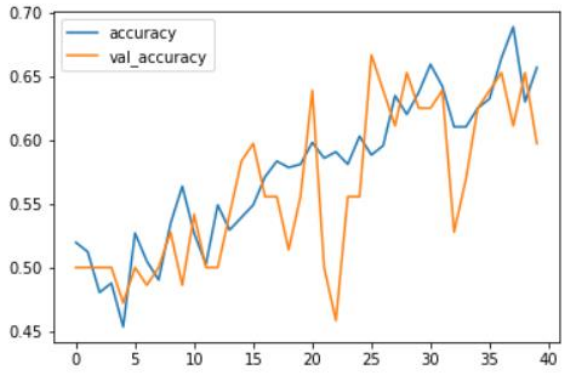


Figure 16(a): Accuracy & Val_Accuracy

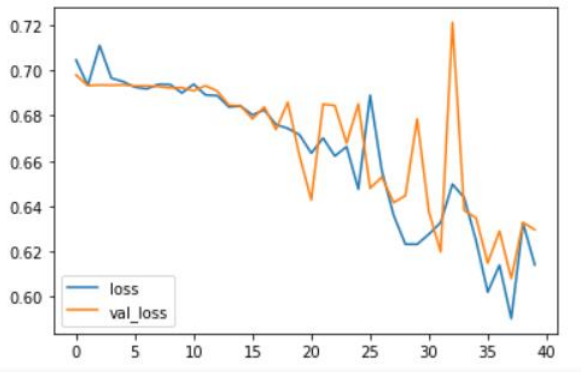


Figure 16(b): Loss & Val_Loss

6 Discussion and Conclusion

The main aim of the research project was to address the severe issues like blindness and vision impairment arising due to adverse ocular disorders. Through this research project an attempt was made to address the problems which could contribute a lot in the medical sector as well as help ophthalmologist to suggest preventive measures which can save a life of an individual. Traditional methods which are used to detect the ocular diseases are, a manual eye health examination which is done with the help of slit lamp biomicroscope. Some of the ocular diseases like cataract and diabetic retinopathy are the dangerous eye disease, if not diagnosed and treated in the early stages can lead to vision problems. Initially, in case of diabetic retinopathy an individual must go through clinical eye examination and if optometrist detects the disease, then again, the patient needs to undergo special test to find out the severity and if an individual needs a surgery or not. This process is tedious for experts and time consuming. Hence a machine learning technique which would diagnose the diseases at the early stage saving a person from impairment and benefitting optometrist from hectic process of detecting disorder. Dataset for the research is taken from open-source platform, Kaggle.

The first step carried out after procuring the dataset is pre-processing of the data. Transformation of image, Feature extraction, Normalization techniques have been applied on the data. Once the data pre-processing was completed, next step in this research project was applying Machine Learning and Deep Learning models to the data. Models applied are Random Forest Classifier, Support Vector Machine (SVM), KNN, and CNN. Performance Evaluation has been done using accuracy score, confusion matrix, precision score, recall score, f1 score, loss and accuracy graph. The Accuracy score of Random Forest, SVM, k-NN are 0.52, 0.59, 0.61. Precision, and recall weighted avg score for random forest, SVM, k-NN are 0.50; 0.52, 0.49;0.61, 0.47;0.59 respectively. Among all these models, the best accuracy score is provided by CNN, i.e., 68 percent. For the performance evaluation, CNN model has given low training and validation loss per epoch.

7 Future Work

There are several things that can be considered and can be done as future work. Right now, the data (open source) available for all the ocular diseases is quite less to work on and implement machine learning and deep learning techniques, in turn which makes it difficult to train data. An individual can approach the clinic or the medical experts and may request for the data to implement the models. Further explorative data analysis can also be performed to find the patterns from the data, for e.g., which ocular disorder, according to the data, is leading to vision impairment and blindness, or similarly can demonstrate which disease in which age group is most commonly seen and so on.

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