Ocular Disease Image Classification Using Deep Learning

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***Abstract*—Everyone in their life span faces eye problem at certain phase, the reasons can be age factor, heredity, or extreme use of phone, laptops that strains the eyes. Many of the eye problems are easy to cure at home but some problems need consulting eye specialist. According to statistics [1] around 2.2 billion people in the world are suffering from Ocular Disease . According to World Health Organisation, the reason behind the increase of eye problems among the people is their lifestyle which includes screen timing. This paper emphasizes on categorising five types of Ocular Diseases like Glaucoma, Cataract, Hypertension, Diabetes, Age Related Macular Degeneration, Pathological Myopia along with Normal eye using Deep Learning algorithms like Convolutional Neural Networks .Using KDD (Knowledge Discovery in Database) methodology and pre-trained neural network models different types of Ocular Diseases are classified and evaluated on the basis of sensitivity and specificity.**

I. Introduction

Every part of the body is important however our eyes are the most essential sensory organs as around 80% of all impressions are recognized by our sight. If in case other senses stops working, eyes are the ones that will protect from danger [2]. If someone is diagnosed with ocular disease, it could be any of the eye related conditions. Because many of the ocular disease shows no symptoms till it gets more serious. To avoid this one should do regular eye check-up. Common Ocular Disease includes Age related Macular Degeneration, Cataract, Glaucoma, Hypertension, Diabetes etc [3]. The normal cost of visiting Ophthalmologist is very high and not everyone can afford it. Most of the eye diseases are caused due to age factor, as the age increases developing cataract is most common in old age people. In modern time, Deep Learning algorithms which is part of Machine Learning which is concerned with the applications like image processing, Natural Language Processing, Video Processing etc. been enhanced to detect certain pattern in the image, one of the exercises is to detect Ocular Diseases.

This paper focuses on five different types of Ocular Diseases images like Diabetes, Glaucoma, Cataract, Hypertension, Age Related Macular Degeneration, Pathological Myopia are classified on the basis of normal eye images.
• Galucoma: In Glaucoma the nerve connecting the eye and the brain that is optic nerve is damaged. The reason behind this damage is the outflow of the fluid in the eye.
• Age related macular degeneration: This occurs with ageing as it causes damage to macula as seen in fig.1 [24] and blurs the central vision.

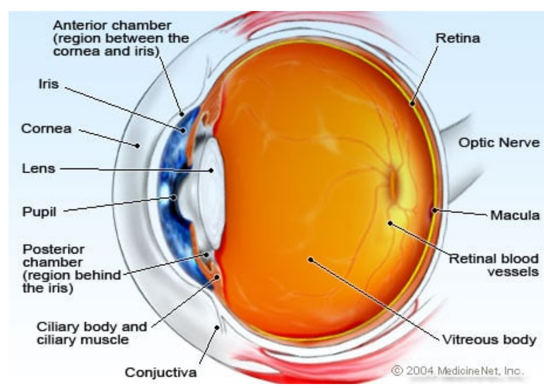

Fig. 1. ResNet Undersampled

• Cataract: A white layer is formed on the lens of an eye, it appears as a cloud.
• Hypertension: While having Ocular Hypertension results in poor flow of fluid present inside the eye and over the time person is more likely to develop Glaucoma.
• Diabetes: It results in the swelling of macula which will cause partial blindness.
• Pathological Myopia: It can be reffered as very short sightedness which is caused due to regressive changes in the back of the eye.

Research Question: How well Deep Learning techniques be used to detect Ocular Diseases?

One of the Deep learning algorithm like Convolutional Neural Network is used in this study. Convolutional Neural Network has the pre-trained models like ResNet-50, VGG, InceptionV3 and EfficientNet. The pre-trained package ResNet-50 is a neural network of 50 layers deep and so it able to classify around 1000 of categories of images. As in this paper,using ResNet-50 different types of Ocular diseases are classified. ResNet-50 is an acronym for Residual Networks is a standard neural network model which acts as a backbone for various projects related to computer vision. The image classification is done using ResNet-50 as it is a classic model and trained again on the images of Ocular Disease dataset and evaluated using sensitivity and specificity of the model.

This paper is structured as follows: Section II demonstrates the literature study done in order to get an idea and proceed with this paper. Section III illustrates the detailed methodology which has been followed with image processing and Section IV is the discussion about the results achieved and their evaluation using different evaluation methods like Precision, accuracy etc. Section V is concerned about the conclusion of this study and the future aspects of the same.

II. Literature Review

A. Pathological Myopia

A research was found on "AUTOMATIC DETECTION OF PATHOLOGICAL MYOPIA AND HIGH MYOPIA ON FUNDUS IMAGES" [4], where by combining Binary Cross-Entropy loss with Triplet loss, the author was able to enhance classification accuracy as author states that the distinction between pathological myopia and high myopia has received scant attention. Thus, author proposed a network which classifies normal vs abnormal and the other classifies high myopia & pathological myopia. The author's approach gave 81.82% accuracy as well as this research paper was helpful to understand how to combine Binary Cross-Entropy loss with Triplet loss but on the other hand one limitation was found that the author did not consider other eye disease.

Similarly, another research was found on Pathological Myopia [5] using different approach that is feature selection. To discover the optimized classifier, an mRMR optimized classifier is trained using the candidate feature set. The proposed methodology was tested on the ocular records of roughly 800 participants from a population research and the experimental findings show that the new classificatory is very effective when features are set at less than 25% of the first candidate. The black box nature of supervised learning is one of its drawbacks as well as other ocular diseases are not considered. Also author themselves states that other eye disorders, such as cataracts and retinopathy, can be treated using the suggested technique.

This paper [6] reports on research that was conducted to automatically classify photos that contain retinal abnormalities and those that do not and are healthy using deep learning approach. The model was put to the test on two datasets, one of which included genuine patient retinal fundus photographs from a resident hospital and 96.5% to 99.% accuracy was obtained. The limitation of this paper was that the author did consider other eye disease, which aids to be opportunity for this project.

B. Glaucoma and Diabetic Retinopathy

Glaucoma, a kind of Diabetic Retinopathy, is a disease that causes vision loss by distorting the optical nerve system. A study [7] was found on Glaucoma disease classification with machine learning approach and got 85% of accuracy. A thorough review of the literature was undertaken by author on pre-processing, feature mining and selection and data sets utilized for testing and training. They've used OCT images as these images have ability to extract detailed information about the interior structure of the eye and forecast glaucoma symptoms. The limitation of this paper was they've used small dataset as well as other ocular disease were not considered, overall this paper motivated to use deep learning approach as the author of this paper haves machine learning approach.

The author studies [8] the use of fractal analysis (FA) to forecast glaucoma progression. A box-counting method as well as a multifractional Brownian motion method that integrates texture and multiresolution studies are used to derive FA characteristics. The accuracy rate of the author's FA feature-based multiclass SVM approach is 0.88, compared to 0.82 and 0.86 for WFA and FFA, respectively. This paper eased to understand box-counting method and multiclass classification and on the other hand there was only one limitation of this research that the author did not consider other ocular diseases which overall became opportunity for us. Similar paper [9]was found where the researcher had used fractal dimension for feature extraction and but used Random Forest for classifying for Diabetic Retinopathy disease. One more paper [10] used machine learning techniques such as (Naive base classifier, Decision tree, KNN, SVM, Naive Bayes Classifier) to detect diabetic retinopathy. This was a survey paper which gave a vast idea & knowledge about Diabetic Retinopathy as well as degree of accuracy of the machine learning techniques. However, a study [11] proposed deep neural network model that aids in the early detection of diabetic retinopathy and glaucoma. The author got 80% accuracy and for future work the author suggests that by tweaking the parameters and using techniques like cross-validation, the accuracy can be enhanced even more. Thus, this paper aided that we can use deep learning as it is more efficient compared to machine learning approach. To get more clear idea about deep learning approaches, another paper [12] was studied where they have worked with fundus images and used ResNet CNN model. So, the author's proposed framework includes three steps. The images are first pre-processed with intensity levelling and enhancement. Second, a ResNet CNN model is used to generate a compact feature vector for grading from the pre-processed image. Finally, to detect DR and establish its severity, a classification step is performed.

C. AMD

The usefulness of transferring picture characteristics computed from pre-trained deep neural networks to the problem of AMD detection is investigated in this study [13]. Over 5600 pictures from the NIH AREDS dataset were used in the tests and got accuracy around 92% and 95%

Similar paper [14] was studied who did transfer learning with over 150000 images, this paper used quite large dataset which was helpful for this project to understand how to work with large dataset as well as how the transfer learning can be beneficial. This research used VGG16 neural network and divided images into two groups, AMD not detected and AMD detected. VGG16 gave promising results, thus it was considered in this project.

In this paper [15] the author demonstrates how to detect drusen in retinal fundus pictures. Then, using RGB and HSV channels, drusen areas are detected using a maximum region-based pixel intensity method. The method is evaluated on 16 fundus pictures from a clinical trial, half of which include drusen. Experiments on the findings reveal that the test picture set has a sensitivity and specificity of 0.75. The limitation of this paper was that the dataset was too small and other ocular diseases were not considered.

D. Multiple eye disease

The use of image processing techniques substantially aids in the diagnosis of a variety of eye disorders. As this project deals with detecting multiple eye disease but of the studies found were dealing with only 1 disease. However, author [18] proposed an approach that can detect age related macular degeneration (AMD), Diabetic Retinopathy, Diabetic hypertension using image processing approach. Therefore, this paper was helpful to understand how to detect multiple eye disease. Similarly, author [19] proposed an approach to detect Glaucoma, Pathological Myopia (PM), and Age-related Macular Degeneration (AMD) using sparse multi-task learning approach. Also, author [20] used ResNet50, InceptionResNetV2, EfficientNetB0 and EfficientNetB2 for detecting ocular disease. This research was helpful for understand various algorithms also it was witness that these results were efficient and can be used in this project

E. Cataract

authors [21] [22] had used deep learning approach to detect cataract eye disease but using different feature extraction and classification like VGG, ResNet and Softmax [23]. Among these, it was witnessed that Resnet and softmax gave promising results thus it was used in this project.

F. Hypertension

As well as authors [16] [17] have used deep learning technique to detect hypertensive but using different approaches like Boltzmann machine classifier, Resnet, VGG, GoogleNet etc and it was observed that Resnet offered favourable outcome. Again with these researches it was confirmed that Resnet can be used in this project.

III. METHODOLOGY

The KDD Methodology[1] which is the acronym for 'Knowledge discovery in Databases' was followed and employed for this data mining study, and it was chosen instead of CRISP DM Methodology as it represented our research question in much better sense as the research question tries to answer that how deep learning methods can be applied for detection of eye diseases and falls under Health care category, the steps followed to answer the research question were then according to KDD Methodology, The steps followed in the KDD Methodology are illustrated in Fig 2 [25]

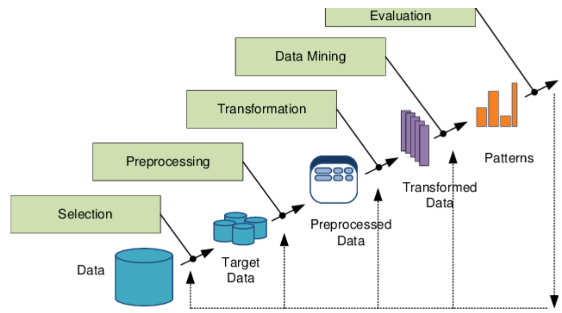

Fig. 2. KDD Methododlogy

A. Data Selection

Through reading the related works we realized that the way in which disease detection is currently done through fundus images, currently the doctor takes and examines the photos of the eye one by one and manually, thus In order to train our classification model, we have chosen different databases that contain this type of photos. Most of the databases that we have found only classified one or maximum two types of eye disease, for example, diabetes or cataracts, these were the most common that we could find, those databases were not of much help since our goal was to train a model that could identify multiple diseases at once. After a rigorous search we found our first database "1000 Fundus images with 39 categories" which, as its name explains, this database is comprised of 1000 images with 39 different classifications, but this database was too small for our purpose. and the balance of data was very remarkable, so we discarded it and continued in search of a more suitable database for our purpose. Finally, we found "The Ocular Disease Recognition" dataset[2], one of the best structured databases we could find and it includes a considerably reliable number of picture to train our model. Ocular Disease Intelligent Recognition is a systematic ophthalmology archive that contains information approximately 5,000 individuals, including their age, color fundus pictures of both eyes, and physicians' clinical diagnosis. The collection is intended to reflect a real-world collection of clinical data gathered by Shanggong Medical Technology Co., Ltd. from various health care centres facilities across China. Fundus

[1]https://www.datascience-pm.com/kdd-and-data-mining/

[2]https://www.kaggle.com/andrewmvd/ocular-disease-recognition-odir5k

photos were taken at some of facilities using a variety of cameras on the market, including Canon, Zeiss, and Kowa, leading in a range of photos sizes. The labels were tagged by qualified human viewers under the watchful eye of a quality department Experts categorize patients among 6 categories, including following:
- Normal Fundus
- Macular Degeneration
- Pathological Myopia
- Glaucoma
- Hypertensive Retinopathy
- Diabetic Retinopathy

B. Data Integration

The original data for the research study to detect the ocular diseases using deep learning models was extracted from kaggle, The Flow Diagram in Figure: 3 illustrates the flow of data after selection of the dataset to extract and using it in the Google colab environment. the end goal of this approach was to directly integrate the dataset from kaggle to google colab. For the step in Data integration , i.e. after selecting the appropriate dataset, A kaggle API key was generated which can be easily implemented using the tutorials from kaggle, The Kaggle API is unique for each kaggle account to authorise the access to the plethora of datasets hosted on kaggle, using google colab as the environment for python jupyter notebook the dataset was programatically downloaded into the google drive of the users account.

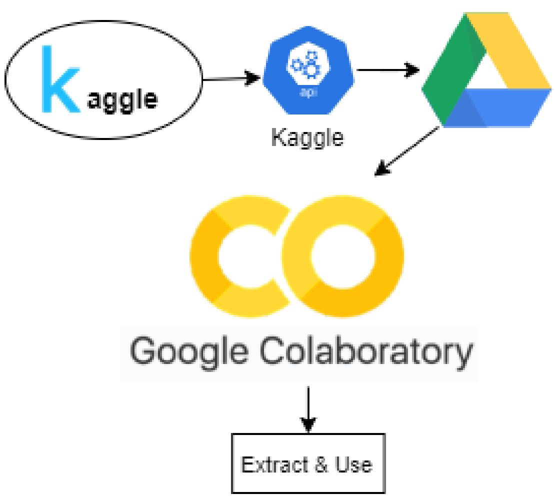

Fig. 3. Data Integration

In order to implement this approach libraries like kaggle and sklearn were used. A directly in the google colab envioronment is then created 'mkdir' command as the google colab uses linux architecture and the json file generated by kaggle API was then uploaded and copied to the appropriate directory along with changing the access to use the json file to everyone. The next step was now then to download the dataset directly from kaggle using the API we just implemented by giving the URL link of the dataset in kaggle download command. After the successful download of the dataset into the google drive it was read and extracted into the google colab environment and was now ready for the initial EDA and cleaning stage.

C. Data Cleaning

The Data Cleaning phase is one of the most important phase in a data mining project, as without properly cleaning and transforming the data into appropriate format, the model trained on that data might not perform as expected. For this research study, after successfully extracting the raw dataset into the coding environment, the various data cleaning operations can be performed on it. Initially all the tags and image paths were read and stored in a dataframe and were renamed accordingly. The major problem with the dataset, is that there were binary columns having values either 0 or 1. Value of 1 Specifies True for disease and 0 specifies False but it does not specify which eye has the disease, in order to handle this problem we are read the labels for each eye separately. The next step was to select all the specific ocular diseases from the dataset, as this study is a multi-class classification problem, we included the following ocular diseases 'pathological myopia' 'glaucoma' 'dry age-related macular degeneration' 'hypertensive retinopathy' 'wet age-related macular degeneration' 'diabetic retinopathy'. Two columns which are 'wet age-related macular degeneration' and 'dry age-related macular degeneration' were merged together. The dataset was then checked for null and missing values, but there was no null or missing rows in the dataset. The dataset then contained 3599 rows of data. The Dataset was highly imbalanced as the normal eyes class had mire than 2800 images and all the other classes had close to 300 images , thus there was a need of balance, in order to achieve the balance first the majority class i.e. normal eyes were undersampled i.e. 300 images were randomly selected from the original dataset, still the classes were not balanced, two alternative models were trained on datasets with image augmentation and oversampling of minority classes . After balancing the dataset, it was then split into training and testing sets with the ratio of 80 percent and 20 percent respectively.The Figure: 4 illustrates the class imbalance in the dataset, and the Figure:5 illustrates the balance of classes after oversampling the minority classes.

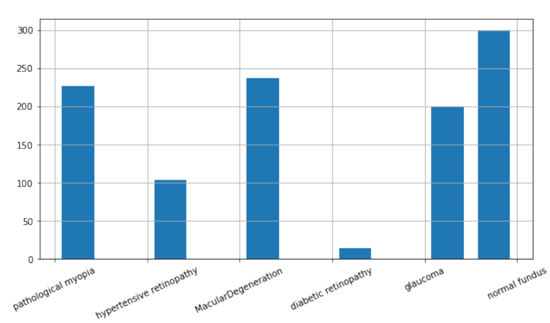

Fig. 4. Class Imbalance

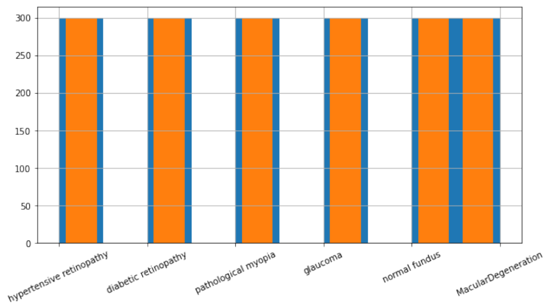

Fig. 5. Class balance after oversampling

D. Data Transformation

After having our data frame ready with all the images and labels that we intend to use, we proceeded to use the flow_from_dataframe() function, this function helps us to read all our images from the directory that we specify, for this, the main parameters we sent to the function was the data frame and the directory, and since in this case we have more than several categories of output, we have to specified that the class_mode was equal to categorical in order to obtain all the different labels. To complement this, this function is based on an image generator which is responsible for augmenting the photos with the following parameters: width_shift_range equal to 0.2 to shift horizontally, zoom_range equal to 0.2 to apply zoom, horizontal_flip equal to True to horizontal flip and finally we specify the brightness_range=[0.2,0.8]. Finally, as every good data preparation we have to specify the data partition that we want for the training and validation of our model, most of the studies use a division of the total data into 80 percent for the training and 20 percent for the validation, therefore we decided to use this same ratio.

E. Modelling

For the modelling part we have used a sequential approach where different paths were adopted to tackle the data imbalance, as the number of records for the normal eye were significantly larger than other eye disease classes, we first randomly undersampled the majority class using the undersampled method from imblearn package.

The Restnet50 pretrained model is used along with additional layers are custom taylored to tackle the multiclass classification problem, The Figure: 6 illustrates the architecture of RestNet50 model, it has 48 convolutional layers for learning. It is a pretrained model on the images which makes it very fast and efficient when using for classification problem. The architecture of the RestNet50 model includes 4 stages.Each stage works as a feedforward network.

The first model, which is RestNet50 was trained on this undersampled dataset, the images were under scaled to 256 pixels this is because, considering the scope and timeline of the study it is not feasible to run the deep learning model on relatively higher resolution images as it takes significantly higher computing power and resources like memory and disk space. The base RestNet50 model was downloaded into the

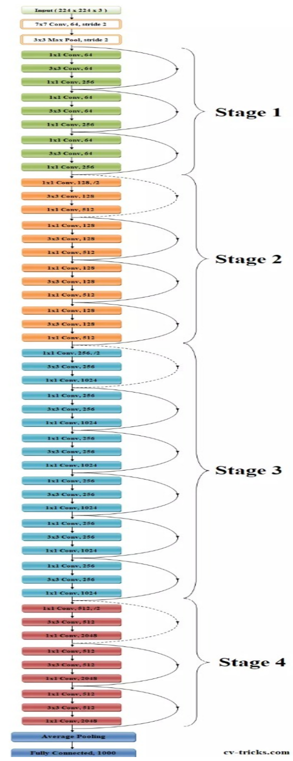

Fig. 6. ResNet-50 Architecture

environment and then additional model parameters were set to cater to the needs of this particular study, After adding these additional parameters for the specific study the model was fit on train dataset along with the validation set. The results of this model is explained in results Section, The second version of model was trained on the same undersampled model, but now all the minority classes were oversampled to achieve the class balance in the dataset, again additional parameters were set on top of the base RestNet50 model, it was observed in the previous model, the recall and precision were not increasing with increase in epoch and thus, the number of epochs were changed to 10. The Results of this model are discussed in the results section, However oversampling each of the minority class is executed by essentially reusing the images from minority class and thus it can cause bias in the model and needs to be addressed.

The Third model, which was trained was on the dataset, where to handle the class imbalance instead of oversampling, Various image augmentation techniques were employed. The first data augmentation method used was width shift, where the width of the training image is randomly change to include more samples in the minority class, the next method used was zoom range, where the input images are randomly zoomed in and out to create more samples of images which are distinct from the original images, the next data augmentation method used was horizontal flip, where random input images are randomly flipped horizontally to create samples of different images, the last data augmentation method used was brightness range, this method changes the brightness level in the input image randomly based on the given input range.

F. Result and Evaluation

The result of the trained models are discussed in this section. As this study tries to answer the question that how deep learning techniques can help in detection of eye diseases, The accuracy cannot be used as a good measure of evaluation , because we want to know how effectively the model can detect specific true positives in the study but not the overall prediction accuracy of the model. The Specificity measures how good the model is on predicting the true negatives in the input and the sensitivity specifies how good the model is in predicting the true positives in the input.

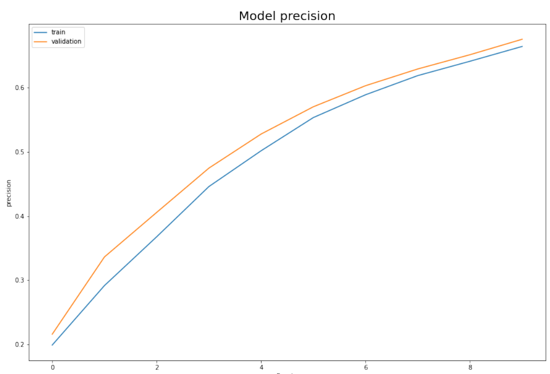

Fig. 7. ResNet Model Specificity

This is the reason we have chosen the sensitivity as our primary evaluation metric, as it helps to detect if the person has a eye disease and then the patient can have treatment accordingly, and this is also the reason we have selected sensitivity over specificity as we are much more interested to detect a patient who has an eye disease over the person who does not have an eye disease. The first version of ResNet-50 model we ran on the dataset on which the majority class was randomly under-sampled did not represented reliable results, the Figure 7 illustrates the model precision/ specificity on train and validation set of data and 66 percent of precision was obtained,

the Figure 8 illustrates the recall/sensitivity on the train and validation set of data, as can be observed from the figure the sensitivity percentage was increasing with increase in epochs, essentially epoch is the number of passes of the entire dataset in the machine learning model. The sensitivity percentage of 49 percentage was obtained at the end. The Figure 9 illustrates the loss function of the model on this dataset, loss function can be defined as the measure of how far the predicted values are from the original values. The loss percentage of 49 percent was obtained. These results are still not reliable and there was clearly a need of improvement.

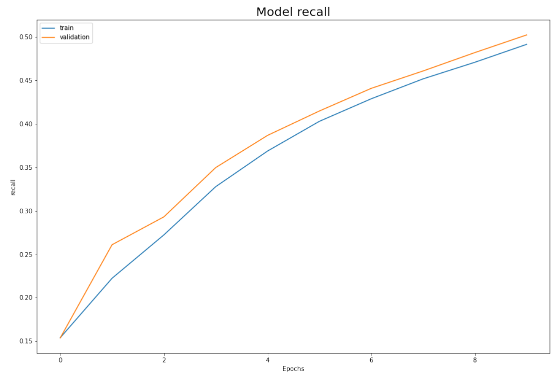

Fig. 8. ResNet Model Sensitivity

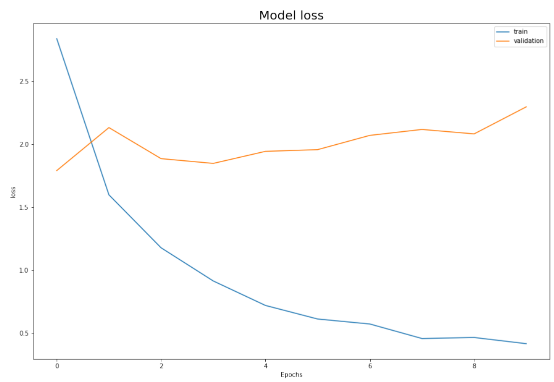

Fig. 9. ResNet Model Loss Function

The Second Model we ran was on the dataset where all the minority classes were oversampled to achieve the balance in the classes, However the major disadvantage of this method is it can introduce bias in the model because to achieve the balance in the dataset, the oversampling method randomly reuses the available images in the minority classes. The accuracy of 95 percent is achieved but this only represents that the model is overfitted, The specificity of 76 percentage along with sensitivity of 61 percentage was achieved respectively. However this model seems to be in overfit state a third model was employed.

The Third model was employed directly addressing the issues with the previous models, the image augmentation approach was used to address the class imbalance in the dataset, as observed in the previous models the sensitivity was still increasing after the 20 epochs, so 30 epochs were used in the model, as the Fig: 10 illustrates the final sensitivity of 58 percentage was obtained, the model recall was increasing sequentially with the increase in each epoch. The Specificity of 77 percentage was obtained as represented in Figure: 11, and the loss function as illustrated in Figure: 12 also decreased significantly to 28 percentage which signifies the difference between the predicted values and actual values were less. These results obtained are reliable and bias free as all the appropriate data preprocessing techniques were used. The results signifies that approximately 58 percentage of time our model can classify the multiple classes of eye diseases from the input image.

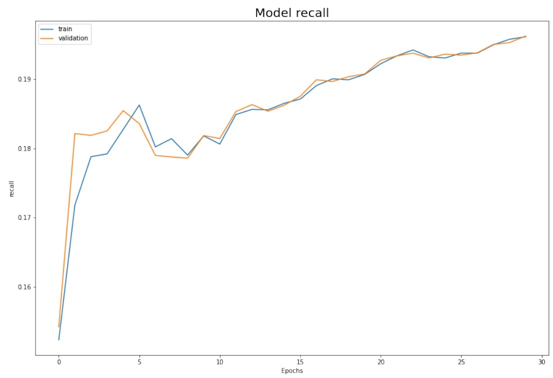

Fig. 10. ResNet Model Sensitivity

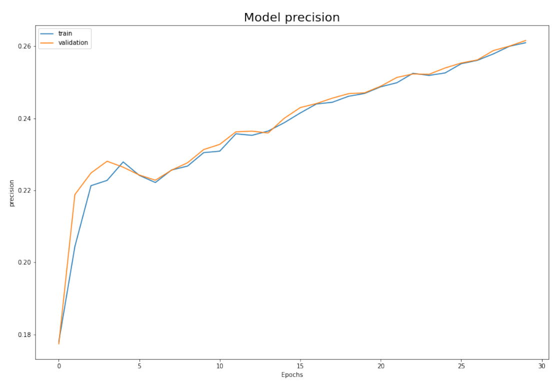

Fig. 11. ResNet Model Specificity

Fig. 12. ResNet Model Loss Function

After evaluating the results obtained on the best fit model, the research question that ”How well Deep Learning Techniques can be used to detect ocular diseases” is answered with the results that we were able to classify multiple categories of eye diseases along with detection of healthy eyes with the sensitivity percentage of 58. The sensitivity could further be increased with the usage of more heterogenous dataset and by increasing the volume of the dataset used as input to train the model.

IV. Conclusion and Future Work

Through this study it can be concluded that various kinds of Ocular Diseases can be classified using Deep Learning approach and through concept of Neural Networks. As opposed to studies found in related work where most of the studies were able to detect one ocular disease or two, this project was able to detect and classify 5 different type of diseases. With the aid of related work, it was observed that ResNet and SoftMax were performing well, so they were experimented and implemented along with VGG but VGG did not perform well as it was very deep and complex base model. Thus, Resnet50 was used for base model, as it is pretrained with 50 layers of neural network and additional layers were custom added for training the model and however we got the best results.

For future work, multiple disease can be detected using one eye through image segmentation and same dataset can be used. The dataset contained some images with low resolutions, so in order to fix resolution issue we could have used Generative adversarial networks (GAN) to increase the image resolution. However, due to time constrained we were not able to use GAN to increase the resolution but in future work it can be considered.

V. Prerequisites

Various packages like Keras, MatplotLib, Numpy , Pandas, CV2 and Seaborn needs to be configured. The kaggle API is required to be generated for the account from the Kaggle website, in order to download the dataset directly from the kaggle website.

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