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Classification of Eye Diseases and Detection of Cataract using Digital Fundus Imaging (DFI) and Inception-V4 Deep Learning Model

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***Abstract*—Ophthalmologists use retinal imaging to diagnose a variety of eye disorders, including microvascular retinal disease, which arises in consequence of high blood pressure and diabetes. Periodic ophthalmoscopy is the most effective method of screening for eye diseases. However, the scarcity of ophthalmologists is a barrier to beginning inspection. The existence of digital fundus cameras for automated image processing can assist ophthalmologists in diagnosing eye illness. Cataracts, glaucoma, and other retinal diseases are the most prevalent causes of age-related eye disorders and vision deterioration in the elderly. The adoption of a computer-based intelligent approach for the categorization of various eye disorders is extremely beneficial in both diagnosis and disease prevention. This study describes a deep learning-based categorization approach for four types of digital retinal images (DRI). Invariant of Inception v4 model is tested on a Kaggle database of 602 DRI of 1.67 GB. We achieve a 96% accuracy rate, and the findings are extremely encouraging.**

Keywords— Deep learning, Digital fundus imaging, Kaggle, Cataract, Glaucoma, Classification, Eye diseases

I. INTRODUCTION

The eye is a tangible organ. It gathers light from the noticeable world around us and converts it into nerve impulses. The optic nerve communicates these signals to the cerebrum, which frames a picture so subsequently giving sight. Natural eyes essentially comprise two globe-formed constructions, the eyeballs, which are encircled by the hard attachments of the skull, the orbits. The orbits are covered with greasy and sinewy tissue to ensure the protection of the eye. Extra designs ensures that eye incorporate with the eyelids, the external covering layer of the eye (stringy tunic), the conjunctiva, and the lacrimal organs. Six extraordinary muscles that addition at various locales outside the eyeball cooperates to control eye development. Each eyeball houses the accompanying parts of the eye: the three covering layers: the external, center, and inward layer as shown in Fig.1 .

The major eye diseases discussed in this research are cataract (100 samples), glaucoma (101 samples), and retinal diseases (100 samples). These samples are to be compared with the normal samples (300 samples). A cataract is a thick, black spot that accumulates in the center of the eye's focus. It starts when proteins in the eye structure cluster collectively, making the focal point incapable of transmitting clear pictures to the retina. The light that flows through the perspective is converted into signals by the retina. It transmits information to the optic nerve, which subsequently transmits them to the cerebrum. Cataracts form gradually and finally obstruct your vision. Glaucoma is a set of eye disorders that cause damage to the optic nerve, which is necessary for normal vision. This type of injury is frequently produced by an extremely high pushing factor in your eye. Glaucoma is one of the most common causes of visual loss in those over 60. It may happen at any age, although it is more frequent in elderly people. Many forms of glaucoma have no warning symptoms. The effect is so constant that you may not detect a change in vision until the disease has advanced to a severe level. The retina is the light-detecting tissue that dwells toward the rear of the eye. It is liable for handing off pictures to one's mind. Without a sound retina, a person can't peruse, drive, or see fine subtleties. A retinal problem or infection influences this vital tissue, which, thus, can influence vision to the place of visual impairment. Normal retinal conditions incorporate floaters (spots in the vision), macular degeneration (central sight loss), diabetic eye illness (blurry or double vision because of diabetes), retinal separation (flashes or floater occurring in the eye), and retinitis pigmentosa (rod-cone disease, Bardet-Biedel syndrome, etc.). Different issues can happen, yet these conditions are the absolute generally normal and genuine that an individual can insight.

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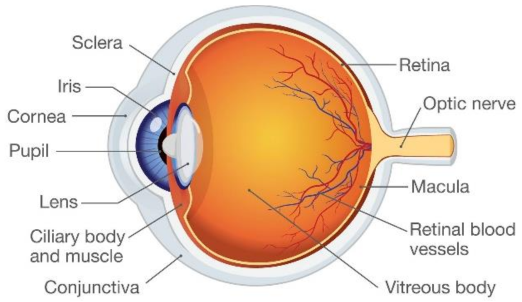

Fig. 1. Internal Structure of Eye [1].

II. LITERATURE REVIEW

In [1], authors layout the standards, strategies and calculations utilized in the computerized discovery of diabetic eye illnesses. The new strategies used to identify fundus picture highlights like the optic circle (OD), fovea and retinal veins, pathologies like hemorrhages, Micro aneurysms (MA), cotton fleece spots and retinal exudates are talked about. They examined the mechanized identification of diabetic eye infections utilizing picture techniques. This paper investigates the benefits and bad marks of the current robotized procedures for the distinguishing proof of retinal highlights and pathologies. In paper [2], analysts present a specialist framework for diagnosing eye sickness based on Naive Bayes. The created master framework applies Case-Based Reasoning (CBR). Naïve Bayes is utilized as a technique for arranging eye infections by applying Bayes' hypothesis. In view of the test results, the Naïve Bayes based master framework achieved 82% precision. Article [3], presents CASDES(A Computer-Aided System to Support Dry Eye Diagnosis), a framework to help the determination of dry eye disorder. Besides, CASDES is likewise helpful for finding eye sicknesses, for example, meibomian organ brokenness. Analyses show the strength of this novel apparatus, which outflanks the past endeavors to make tear film maps and furnishes solid outcomes in examination with the clinicians' explanations. [4] depicts the use of picture handling procedures for programmed recognition of eye sicknesses. Huge rates of individuals experience the ill effects of eye infections in rustic and semi metropolitan regions in. Picture handling procedures enormously help diagnosing different eye sicknesses. Ebb and flow finding of retinal sickness depends firmly upon optical imaging techniques because of the photon detecting nature of the eye over a wide band of frequencies. The key picture preparing components to distinguish eye illnesses incorporate picture enlistment, combination, division, highlight extraction, improvement, design coordinating, picture characterization, examination and factual estimations.

[5] presents a precise overview of mechanized ways to deal with diabetic eye infection identification with help of few angles, specifically: i) accessible datasets, ii) picture preprocessing procedures, iii) profound learning models and iv) execution assessment measurements. The study gives an extensive outline of diabetic eye recognition and significant understanding into research networks, medical services experts and patients with diabetes. In [6], creators fostered a robotized framework to diminish the time and responsibility for ophthalmologists and utilized best two pretrained convolutional neural organization (CNN) models on ImageNet. In [7], analysts proposed technique to analyze the waterfall and conjunctivitis eye infections by calculation approach and guarantees extraordinary outcomes. The calculation can possibly facilitate the strain on optometrists and eventually the general public.

[8] presented a technique for grouping tear film pictures dependent on surface examination utilizing phylogenetic variety files and Ripley's K capacity. The proposed strategy comprises of six primary advances: obtaining the picture dataset; division of the locale of premium; include extraction utilizing phylogenetic variety lists and Ripley's K capacity; highlight choice utilizing Greedy Stepwise; arrangement utilizing the calculations Support Vector Machine (SVM), Random Forest (RF), Naive Bayes (NB), Multilayer Perceptron (MLP), Random Tree (RT) and Radial Basis Function Network (RBFNet); and (6) approval of results. [9] presented a neural network based framework to analyze early eye sicknesses of the patients. They used multi-facet feedforward networks with a solitary secret layer. The Backpropagation calculation is utilized for preparing the organizations in an administered mode and achieved 87% accuracy. [10] proposed a twofold combination strategy dependent on blend rules to work on the grouping of dimensionless lists in petrochemical turning hardware gear. This technique first gathers the first information and tallies the shared dimensionless list as the group of proof. In [11], a learning-based methodology is introduced for the early location of diabetic retinopathy from retinal pictures. The proposed approach comprises of two stages. In the primary stage, pretreatments were performed to eliminate retinal pictures from various informational indexes and normalized. In the subsequent stage, arrangement was made by Convolutional Neural Network. In [12], research objective is to naturally arrange pictures with retinal issues from those of the solid ones without any unequivocal division or highlight extraction. [13] utilized a calculation based model for identifying moles in the natural eye sclera. An eye mole picture is the info picture for the proposed calculation. This information picture is preprocessed utilizing dark scale transformation and a middle channel. The sifted picture goes through twofold change and morphological tasks.

TABLE I. COMPARISON OF PREVIOUS STUDIES.

Research	Diseases	Methods	Results
[1]	Detection of diabetic eye diseases.	Image Processing Method.	Techniques for Identifying Retinal Features: Benefits and Drawbacks
[2]	Eye Disease Classification.	Naïve Bayes Theorem	Accuracy: 82%
[3]	Dry Eye Syndrome.	CASDES (Computer-Aided System to Support Dry Eye Diagnosis).	Accuracy: 90% Sensitivity: 97% Specificity: 86% Precision: 83%
[4]	Detection of Eye Diseases.	Image Processing Techniques.	Easy Detection & Diagnosis of Eye Diseases for Large Number of Patients.
[5]	Diabetic Eye Disease Detection.	Image Processing Techniques and Deep Learning Models.	A comprehensive overview of the state of the art on Diabetic Eye Disease (DED) detection methods.
[6]	Detection of Mild & Multi-Class Diabetic Eye Diseases.	Deep Learning (DL).	Classification Accuracy Multi-Class: 88.3% Mild Multi-Class: 85.95%
[7]	Detection Cataract and Conjunctivitis.	Image Analysis Using OpenCV Library & BGR Color Property.	Classification Accuracy Cataracts: 92%

			Conjunctivitis: 83%
[8]	Classification of Tear Film.	Ripley's K Function and Phylogenetic Diversity Indexes	Accuracy: 92.622% Standard Deviation: 0.843%
[9]	Diagnosis of Eye Diseases.	Neural Network Approach.	Accuracy: 87.1%
[10]	Fault Diagnosis.	Double Sample Data Fusion Method.	Accurately Determination of Fault Types.
[11]	Diabetic Retinopathy Early Detection	Deep Learning (DL) & Convolutional Neural Network.	Accuracy: 98.5%
[12]	Retinal Eye Disease Detection.	Deep Learning (DL).	Accuracy: 96.5%
[13]	Mole extraction from the sclera of the eye.	Object Area Detection Algorithm.	Detection of Mole.

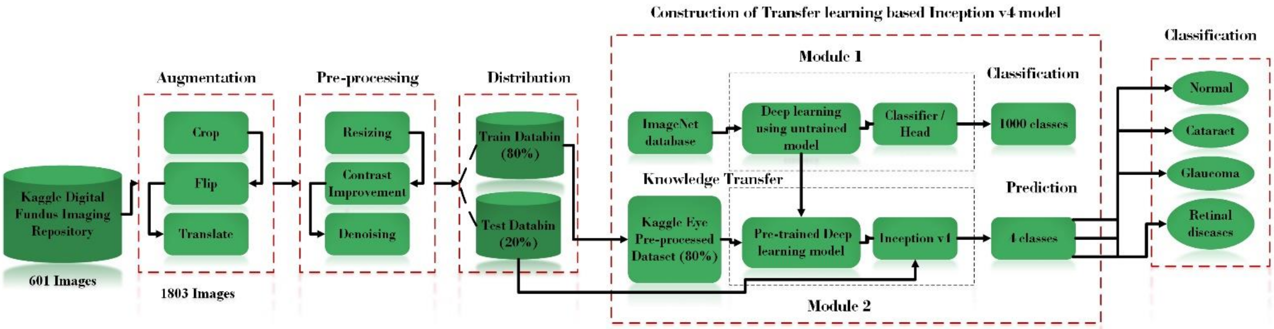

Fig. 2. Block diagram of proposed methodlogy.

Fig. 3. Digital Fundus Imaging System [4].

III. Research Methdology

Eye is a sensitive part of human body so we need to detect the seriousness of eye disease and their types. Block diagram shown in Fig.2 shows a deep learning approach for detection and classification of cataract, glaucoma and retinal disease. This system also successfully detects a normal eye when no disease is found. We trained and tested the inceptionV4 deep learning model with pre-trained weights and different learning rates. Overall best accuracy of 96.6% is achieved by augmented dataset.

A. Dataset Acquition

1) Digital Fundus Imaging: The fundus of the eye consists of the inner surface of the eye towards the lens and comprises the retina, optical disc, macula, fovea and back pole. The funds can be tested using a picture of the ophthalmoscopy. Fundus photos are ocular documentation that shows a patient's retina appearance. For the monitoring of the course of certain eye illnesses, optometrists, ophthalmologists, orthoptists and other qualified medical practitioners utilize fundus photography. Fundus pictures are also utilized for documenting illness abnormalities affecting the eye and/or to track disease development.Fundus photos capture the retina, the tissue in our eyes that converts the optical pictures that are seen to our brains in the electrical impulses. The retina may be directly imaged as the pupil is employed as an entry and exit to the light and imaging rays of the fundus camera. With its neck in a chin rest and its forehead against the bar, the patient sits on the fundus camera. The fundus camera is focused and harmonized by an ophthalmic photographer. The photographer pushes a flash and creates an image of a fundus as shown in Fig. 3. Ophthalmologist’s track, diagnose, and cure eye problems using these retinal images.

2) Dataset: The eye diseases dataset has been obtained from publicly available source Kaggle [19], where normal eye images along with the diseased fundus images of cataract, glaucoma and retina are provided. There is total 601 images available where 300 images are normal and the rest are diseased images. 100 images belong to cataract, 101 images to glaucoma and 100 images to retinal diseases.

B. Dataset Augmentation

Data Augmentation is a technique for artificially increasing the size of a training set by generating changed data from existing data. Here the dataset was augmented by cropping, flipping, and translation of all the raw images as shown in Fig.4 and the detail is listed below,

1) Cropping is the process of removing undesirable portions from an image or illustration.

2) A flipped image is a static or moving image created by mirroring an original across a horizontal axis.

3) During image translation, each pixel of the item must be adjusted in the identical orientation and similar length.The initial object is known as the pre-image, and the item after translation is known as the image.

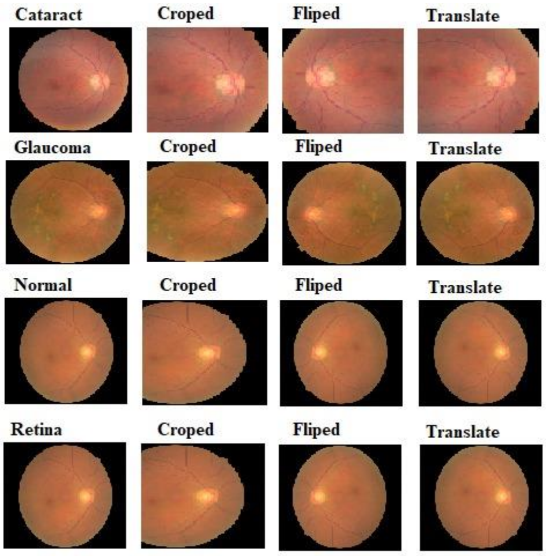

Fig. 4. Augmented Images.

Table II shows dataset statistics before and after the augmentation

TABLE II. DATASET STATISTICS

Subjects	Before Augmentation	After Augmentation
Normal	300	900
Cataract	100	300
Glaucoma	101	303
Retinal Diseases	100	300
Total images	**601**	**1803**

C. Pre-processing

The augmented dataset is pre-processed before given as an input to deep learning model (DLM). Following steps are applied which is also shown in Fig. 5.

i. Each image has dimension of 2592*1728 which has been resized to a fixed dimension of 244*244.

ii. After resizing, contrast enhancement has been applied to each of the image where the quality of the is enhanced so that understanding of each image by DLM could be easy.

iii. The last step of the pre-processing is the removal of the noise from every image. The averaging filter has been applied to each image before input into deep learning algorithm.

D. Dataset Distribution

We randomly separated the dataset into 80% and 20% for training and testing purpose respectively for both augmentation and without augmentation dataset approach.

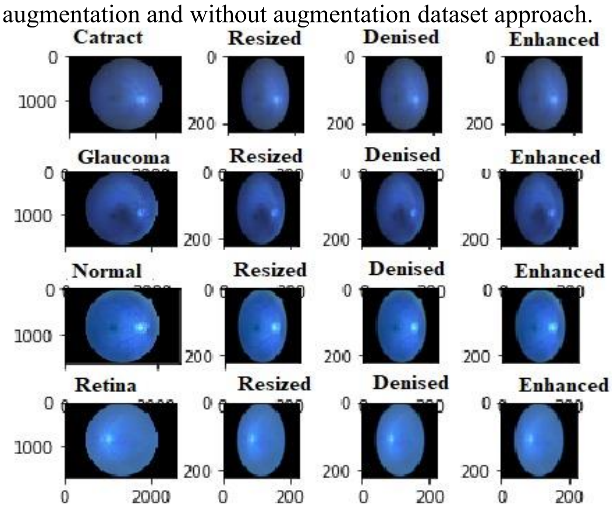

Fig. 5. Pre-processed Images.

E. InceptionV4 Deep Learning Model

Up to 2014, the standard Convolutional neural network (CNN) structure was stacked with convolutional layers, max-pooling, followed by one or more fully connected layers (FCL). This has limitations.

i. Memory footprint is rather large.

ii. High computational demand

iii. Overfitting is a risk.

iv. Gradients that fade and erupt.

Here we used a variant of CNN named as InceptionV4 deep learning model with its pre-trained wights on ImageNet dataset (1000 classes) for the detection and classification of eye diseases. The complete architecture of InceptionV4 is shown in Fig.6. Inception v4 is a deep convolutional network design that has been demonstrated to attain excellent performance at a minimal computation complexity. It is a pure Inception version with residual connections that performs better than Inception-ResNet-v2. Its functionality is comparable to that of the most recent generation Inception-v3 network and its main contribution are as follows:

i. Concatenate all features after filtering the same region using various kernels.

ii. Reduce the computation by introducing a bottleneck as a dimension reduction.

iii. Implement Batch Normalization.

iv. Use a tiny kernel and an asymmetric kernel to make your network more efficient.

v. Smoothing of labels.

vi. Substituted filter concatenation.

vii. Reduced training time.

viii. Potential network "death"—training instabilities

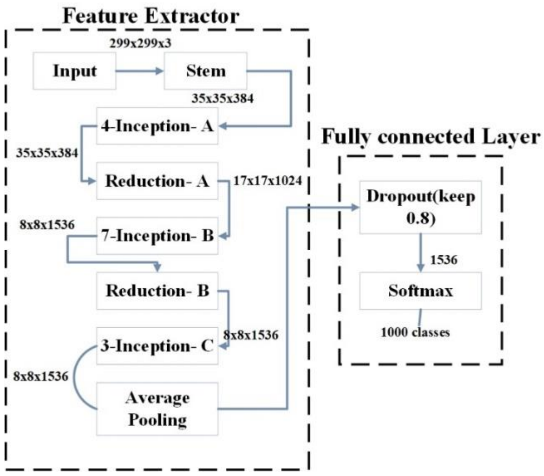

Fig. 6. Block Diagram of Inception v4 Model.

F. *Classification*

Here, the transfer-learning approach is applied to classify four types of digital images (cataract, glaucoma, and retinal) of the digital fundus, i.e., normal and disordered eye images as shown in figure 9 and scientifically examine the effect of DA on DLM and try to address the issue of whether we should increase the data in order for melanoma classification to be more effective. Inception v4 trained using the same features retrieved by its first layers from the augmented and original data sets.

IV. RESULTS AND DISCUSSIONS

InceptionV4 is trained and tested on both augmented and without augmentation images with different learning rates of 0.01, 0.001 and 0.0001, 30 epochs which is further divided into 10 steps with a batch size of 64 images. Adam optimizer is used as a gradient descent. This model is implemented using Keras with TensorFlow on PyCharm. InceptionV4 pre-trained model with different learning rates. Initially learning rate, we kept 0.01 which resulted in an accuracy of 85.03% (augmented dataset) and 95.64% (non-augmentation dataset). Then we improved the accuracy by changing the learning rate to 0.001 and achieved 86.70% and 95.79% accuracy without and with augmented dataset respectively. Finally, model achieved the best accuracy by keeping the learning rate of 0.0001 which is comparatively slowest to train on given dataset as compare to other learning rates. The different learning rates along with achieved accuracy are shown in Table III.

TABLE III. ACCURACY TABLE WITH DIFFERENT LEARNING RATES ALONG WITHOUT AND WITH AUGMENTATION

SR.NO	Learning Rate	Without Augmentation (%)	With Augmentation (%)
1	0.01	85.03	95.64
2	0.001	86.70	95.79
3	0.0001	**86.74**	**96.66**

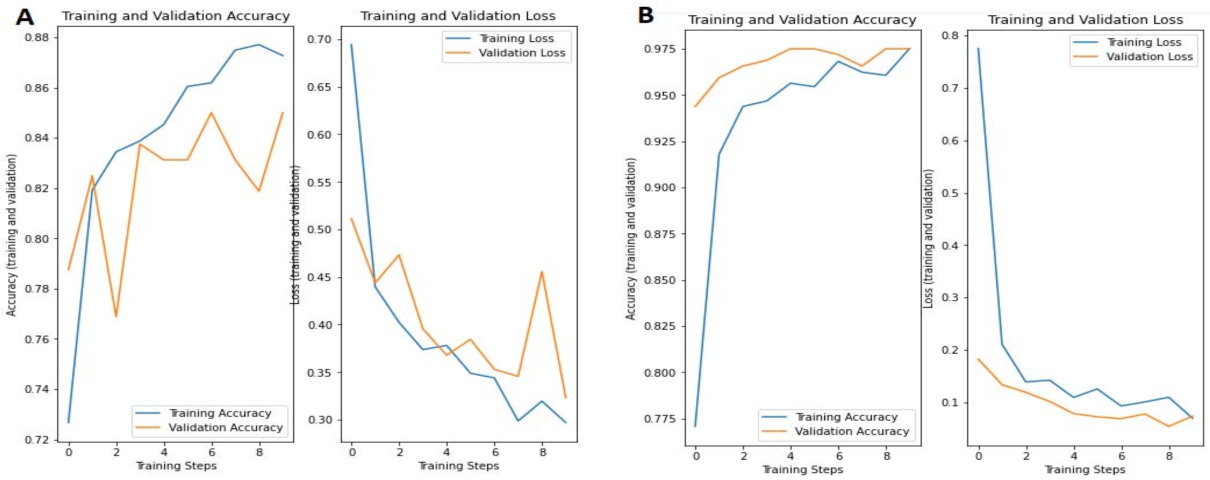

Fig. 7. Accuracy Graph (A) Without Augmentation (B) With Augmentation at learning rate of 0.0001.

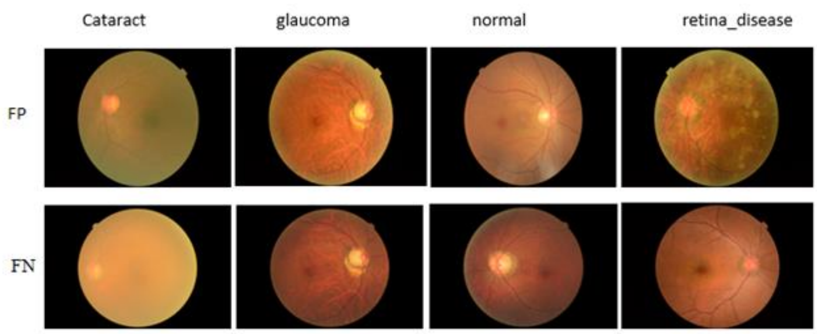

Fig. 8. Samples Having False Positive(FP) and False Negative(FN).

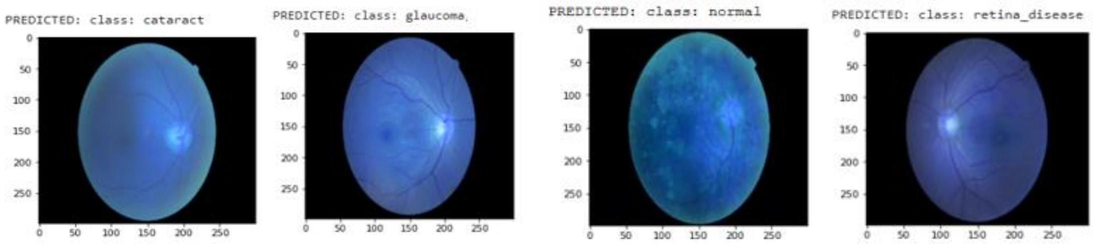

Fig. 9. Model predictions.

Fig. 7 shows the training and validation accuracy graph by keeping the learning rate 0.0001. Fig. 7(A) shows that intially 86.74% accuracy was achieved which was initially low and gradually increased. Whereas validation accuracy was initially low and improves as the epochs increased. Similarly, Fig.7(B) shows the training and validation accuracy with augmented dataset. It can be seen that model has achieved the significant accuracy from the beginning and continuously improved it until last epoch. Fig. 8 shows the results of each class where our model has false prediction. The first row shows the results where model has false positive predictions and the second row shows the examples of false negative predicted by the model. A false positive is an outcome in which the model forecasts the positive class erroneously. A false negative is an outcome in which the model forecasts the negative class inaccurately. Fig. 9 shows model predictions, when randomly test images from each class are given to the model.

V. Conclusion

This article's objective was to create a system that could categorize retinal fundus pictures as pathological or normal. We created a system that reliably conducted multiclass classification using the Inception v4 deep learning model. The pictures of the retinal fundus were taken from the public Kaggle database [19]. We discovered an average accuracy of 96.66% with the augmented dataset and 86.74% without. The model can be improved but this would need collecting a considerably bigger and more diverse set of datasets and training the model for multi-class classification correspondingly. In future, we can explore different deep learning models and provide comparison between all. We can also enhance accuracy by fine tuning deep learning models.

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