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Eye Disease Classification Using Convolutional Neural Networks

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Abstract - The eye is an essential sense organ responsible for vision. Since certain eye disorders can lead to vision loss, it is crucial to diagnose and treat these conditions at an early stage. By identifying common eye diseases and performing regular eye examinations, eye care professionals can help prevent vision impairment or blindness. In this work, Convolutional Neural Networks (CNNs) and transfer learning are used to differentiate between normal eyes and those affected by diabetic retinopathy, cataract, or glaucoma. By applying transfer learning for multi-class classification, our goal is to achieve high accuracy by leveraging pre-trained models on this specific dataset to obtain better results.

1. INTRODUCTION

Patients with vision problems suffer from a significantly reduced quality of life. Diabetic retinopathy and glaucoma are examples of eye diseases. Globally, 64.3 million people had glaucoma in 2014 [1]. Early detection of eye diseases can aid in proper treatment or, at the very least, prevent these conditions from worsening. However, detection is often limited due to a lack of awareness, a shortage of ophthalmologists, and high consultation costs [2]. Hence, automated screening is critical.

This paper will utilize machine learning techniques to distinguish a normal eye from one with a disease. Using eye images, numerous studies have attempted to predict and/or classify a healthy eye versus a diseased one [3], [4], [5]. Porwal et al. presented a robust automated method based on a proprietary CenterNet model and a DenseNet-100 feature extractor for detecting and classifying diabetic retinopathy and diabetic macular edema lesions. They achieved accuracies of 97.93% and 98.10%, respectively, while evaluating their methodology using the APTOS-2019 and IDRiD benchmark datasets.

Chelaramani, S [2] proposed three classification techniques for multiple classes: Convolutional Neural Network (CNN), Visual Geometry Group 16 (VGG16), and Inception V3. Using a confusion matrix, the precision of each method was measured and compared. Grassmann et al. [5] developed an algorithm for categorizing age-related macular degeneration using a substantial collection of color fundus images as their data source. Validation was carried out using a population-based, cross-sectional study. Within the Age-Related Eye Disease Study (AREDS) context, 120,656 color fundus images were manually graded from the eyes of 3,654 participants [5].

In their 2016 paper, Bhatia et al. [6] discussed various strategies for constructing an automated system to detect cases of diabetic retinopathy in people with diabetes. The goal was to provide ophthalmologists with a tool to aid in the early detection of diabetic retinopathy symptoms [3], [4], [7]. Additionally, the study reviewed various technologies used for diagnosing and detecting diabetic eye disease in its early stages.

Diabetic eye disease (DED) classification relies heavily on image processing; thus,Sarki et al. [7] offered a comprehensive study on the subject. Image quality enhancement, segmentation, geometric augmentation, and classification comprise the proposed automated classification framework for DED. The best results were achieved by combining traditional image processing techniques with a newly developed convolutional neural network (CNN) architecture.

When applied to DED classification problems, this CNN combined with conventional image processing methods showed superior performance. The experimental data indicated satisfactory levels of precision, sensitivity, and specificity [8],[9].

In the broader context, the use of labeled datasets such as HRF [10], ODIR-5K [11], and others like the Kaggle diabetic datasets [12] has further enhanced the development and benchmarking of deep learning-based eye disease detection systems. Additionally, recent advances in transfer learning techniques [8],[13], [14], [15] and architectures such as ResNet, VGG, and EfficientNet [16], [17] have significantly improved performance in classification tasks relevant to ophthalmology .

2.Related Work

Convolutional Neural Networks (CNNs) have emerged as powerful tools for automated diabetic retinopathy (DR) classification in recent years. Their ability to learn hierarchical features directly from retinal fundus images has led to significant improvements in accuracy compared to traditional machine learning techniques.

The field of eye disease classification is undergoing a remarkable transformation thanks to CNNs. These AI models are analyzing retinal images with superhuman precision, paving the way for earlier diagnoses and improved patient outcomes. Below are some key research works that showcase the potential of CNNs in this domain:

Deep Learning for Ocular Disease Recognition: An Inner-Class Balance(2022)[18]: This study explored the challenge of imbalanced datasets in ocular disease classification. A student network was trained with guidance from a teacher network, focusing on learning discriminative features for differentiating between rare and common classes.This technique achieved impressive resu-lts, significantly improving classification accuracy for rare eye diseases while maintaining performance for common ones.

ReLayNet: A Fully Convolutional Network for Retinal Layer Segmentation (2017)[19]: This work addressed the challenge of segmenting different layers within retinal images, which is crucial for analyzing diseases like age-related macular degeneration (AMD). The authors developed ReLayNet, a deep CNN architect-ture specifically designed for this task.ReLayNet achieved state-of-the-art performance in segmenting various retinal layers, paving the way for more accurate diagnosis and monitoring of AMD progression.

Optimized Convolutional Neural Network-Based Multiple Eye Disease Detection (2022)[20]: This research focused on developing a single CNN architecture capable of detecting multiple eye diseases simultaneously. The proposed model, named MCNN-EyeD, combined various convolutional and pooling layers with a novel attention mechanism.The attention mechanism helped the model prioritize relevant features, leading to high accuracy in classifying diabetic retinopathy, glaucoma, and cataracts from retinal images. This multi-disease detection capability holds promise for streamlining diagnosis and improving patient care efficiency.

Deep Learning-Based Disc Cup Segmentation Glaucoma Network(2018)[21]: This research concentrated on glaucoma detection by analyzing the optic disc in retinal images. The authors proposed DC-GNet, a CNN architecture specifically designed for disc cup segmentation.zDC-GNet achieved Exce -llent accuracy in segmenting the optic disc, enabling better glaucoma assessment and early detection.

Detection of Retinal Abnormalities in Fundus Images Using CNN Deep Learning Networks (2021)[22]: This study explored the use of CNNs for detecting various retinal abnormalities,including diabetic retinopathy, drusen, and hyperpigmentation. The researchers compared the performance of several pre-trained CNN architectures, such as VGG16 and ResNet50,in classifying these abnormalities.

3.METHODOLOGY AND DATASET

The capability of software or a device to recognize and analyse eye disease is a bit risky thing. Recognition can be performed from both online and offline ways. The initial step is to receive fundus images, which is recognized as image acquisition that will proceed as an input to preprocessing.

The process begins with the collection of a dataset comprising Retinal images, with a focus on cases involving Diabetic Retinopathy, Cataract, Glaucoma. These images serve as the input data for the CNN model. The first step involves the preprocessing of the retinal images, which includes tasks such as resizing, normalization, and categorization to ensure uniformity and enhance the model's ability to generalize. The pre-processed images are then split into training, testing and validation data sets. The core of the methodology lies in the implementation of the CNN architecture, configured to detect Diabetic Retinopathy, Cataract, Glaucoma patterns in the Retinal images. Then, it will extract every characteristic of the features from each image of the character This stage is especially important for eye disease recognition, which is called classification. As shown in Fig 1, the process of eye disease detection using fundus images involves pre-processing, feature extraction using CNN-based architectures, and classification into categories such as normal, glaucoma, diabetic retinopathy, and cataract.

Based on classification accuracy and different approaches to recognize the images, there are many

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classification methods, i.e., convolutional neural networks (CNNs), support vector machines (SVMs), recurrent neural networks (RNNs), deep belief networks, deep Boltzmann machines, and K- nearest neighbour (KNN). In this project we will be using CNN classification model and some transfer learning models.

Once the model is trained, the evaluation phase begins. The testing set of retinal images is fed into the trained CNN model to assess its performance. One of the famous metrics accuracies computed to quantitatively measure the effectiveness of the proposed models.

DATA SET DESCRIPTION

In the dataset chosen there are 4 categories of images. They are normal (class-0) i.e., no disease, glaucoma (class-1), diabetic retinopathy (class-2) and cataract (class-3). As we can see from the **Table:1** the dataset that each class consists of nearly 1000 images.

Table:1 No. of images in each data set.

TYPES OF RETINOPATHY	NO.OF IMAGES
Normal	1074
Glaucoma	1007
Diabetic retinopathy	1098
Cataract	1038

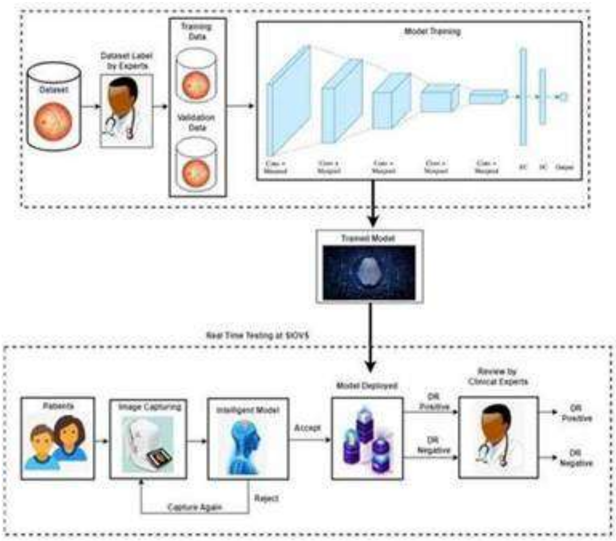

Fig 1: Proposed flow diagram to classify eye diseases from fundus images

In the dataset chosen there are 4 categories of images. They are normal (class-0) i.e., no disease, glaucoma (class-1), diabetic retinopathy (class-2) and cataract (class-3). As we can see from the table the dataset that each class consists of nearly 1000 images.As illustrated in Fig 2, the dataset includes retinal images representing different eye conditions—diabetic retinopathy, cataract, and glaucoma—each displaying distinct visual characteristics crucial for accurate classification

Class distributions in eye disease datasets, where certain diseases like healthy eyes might be significantly overrepresented compared to rarer conditions like diabetic retinopathy. The researchers proposed a novel approach that combined two CNNs:

Teacher network: trained on the entire dataset to learn generalizable features.

We need to split the dataset into 2 parts i.e., training and testing. 80% of the data is used for training of which some images are used for validation. The remaining 20% are used for testing the trained model. To split the data masking is done. Masking removes the labels below the images and the data is split randomly.

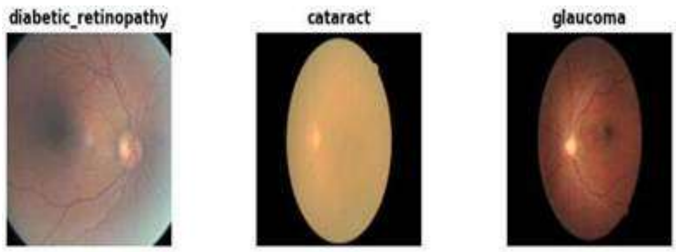

Fig 2: The Three types of eye diseases.

4.RESULTS AND DISCUSSIONS

A total of 100 epochs is given. The learning rate reduced half each time at 20, 24, 32, 36, 40, 42, 44, 48, 53 and 56 epochs respectively. The model stops running at 58 epochs to avoid over-fitting. The initial learning rate given is 0.001 and it reduced till 1.953e-06. The accuracy reached is 0.9317 and the validation accuracy reached 0.9154. As shown in Fig 3 and Fig 4, the CNN model demonstrates effective training with steadily increasing accuracy and decreasing loss, indicating good learning progression. The confusion matrix in Fig 5 further confirms the model's strength, particularly in predicting diabetic retinopathy accurately.

Plot of Training Accuracy VS Validation Accuracy:

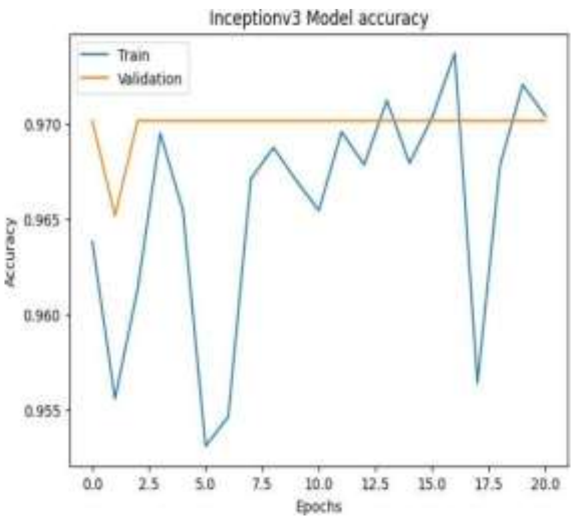

Fig 3: Accuracy plot obtained using CNN Model

Plot of Training loss VS Validation loss:

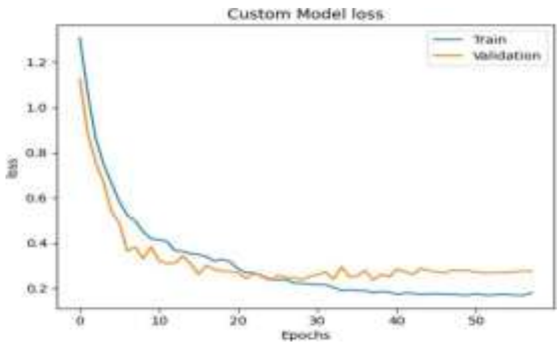

Fig 4: Loss plot obtained using CNN Model

The confusion matrix shows in a table form as to how accurate the model is. Here we can see that the model is able to predict majority of images correctly for all 4 types of images. The label-2 which are the diabetic retinopathy disease images have been predicted much accurately relatively to other labels.

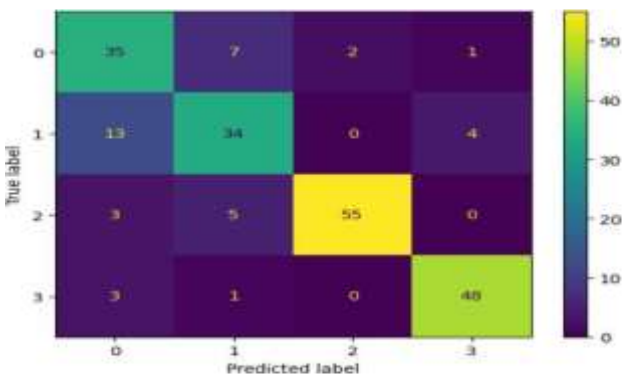

Fig 5: Confusion matrix obtained using CNN Model

INCEPTION V3

A learning rate of 0.01 is given. The learning rate reduced each time at 5, 9, 13, 17, 21 respectively. A total of 100 epochs was given and was coded to early stop to prevent over-fitting. The model stooped at 21 epochs reaching the accuracy of 0.9704 and a validation accuracy of 0.9701 at the learning rate 9.765e-07

Plot of Training Accuracy VS Validation Accuracy:

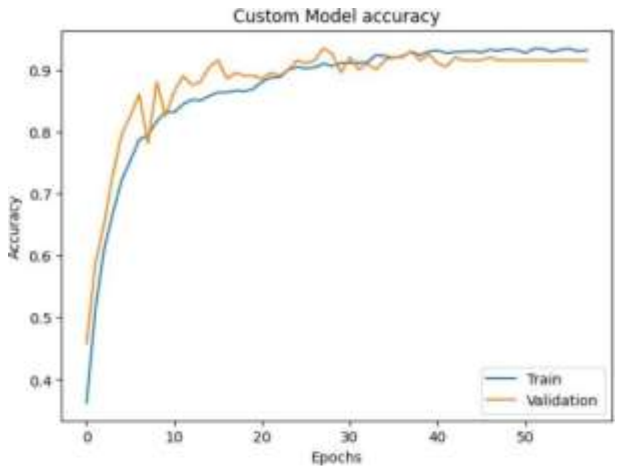

Fig 6: Model Accuracy obtained using InceptionV3 Model

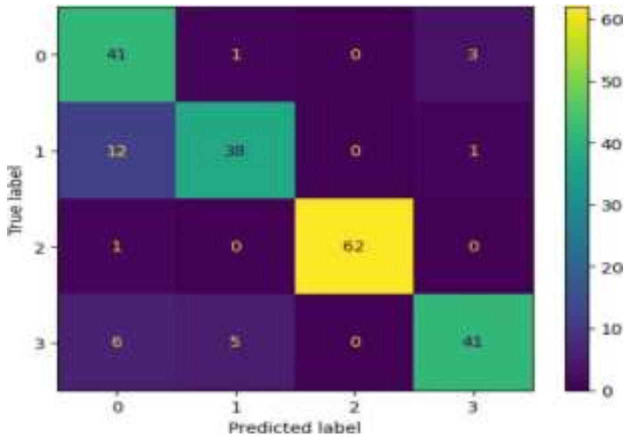

Fig 7: Confusion matrix obtained using InceptionV3

INCEPTION RESNETV2

Plot of Training Accuracy VS Validation Accuracy:

The learning rate given was 0.001 and is reduced to half at 6, 12, 16, 20, 24, 28 epoch each time. Here also 100 epochs were told to run but it stopped training at 28 epochs to prevent over-fitting. It reached an accuracy of 0.9984 and validation accuracy went up to 0.9602. As seen in Fig 6, the InceptionV3 model maintains consistent training and validation accuracy with minimal fluctuation, while Fig 7 presents its confusion matrix, showing strong prediction performance, especially for diabetic retinopathy and glaucoma. Fig 8 further illustrates the accuracy progression of the ResNetV2 model, which demonstrates a smoother and higher accuracy trend, complementing the confusion matrix's indication of reliable predictions across all classes.

Plot of Training Accuracy VS Validation Accuracy:

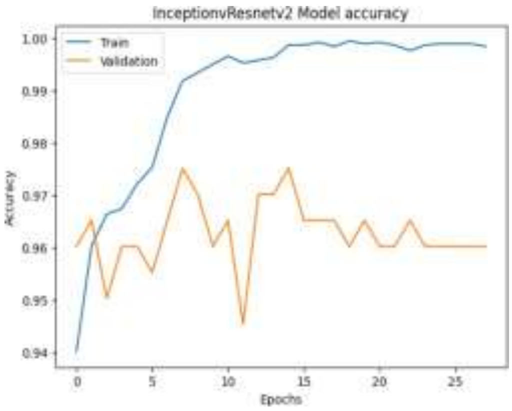

Fig 8: Model Accuracy obtained using RESNETV2

This confusion matrix gives us a visual representation of how accurately the model predicts the test dataset. It is quite similar to the inception v3 confusion matrix as both follow similar method. The label-2 and label-3 that are diabetic retinopathy and glaucoma respectively have been predicted quite accurately relative to the normal eye and cataract images.

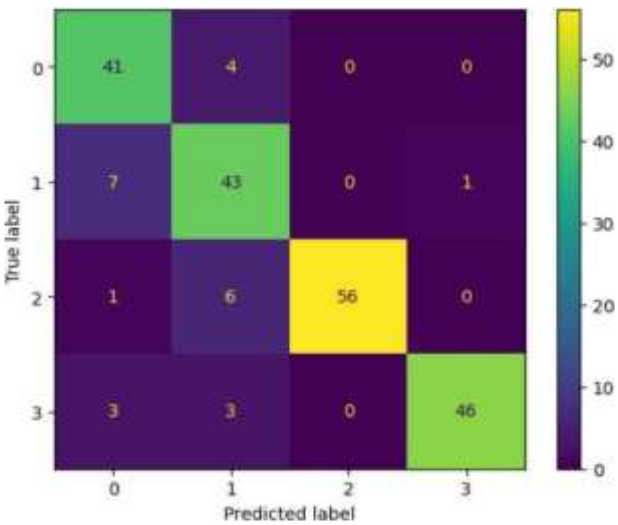

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Fig 9: Confusion Matrix obtained using RESNETV2

Table 2: Results Obtained using different models:

MODEL	Training Accuracy	Validation Accuracy	Testing Accuracy
CNN	0.9317	0.9154	0.8626
INCEPTIONV3	0.9704	0.9701	0.9573
INCEPTIONRESNETV2	0.9984	0.9602	0.9716

5.CONCLUSION

This study attempts to understand specific strengths and weaknesses of common deep learning models in order to identify Diabetic Retinopathy ,Glaucoma and Cataract with acceptable accuracy.

In this work, deep learning techniques were used for automatic Eye Disease detection from Fundus images of Eyes.

The basic CNN model was used and trained into multi-classifiers.

Our work can help ophthalmologists to make better and faster diagnosis which might help to prevent or cure patients before the disease gets severe.

This study demonstrates the effectiveness of deep learning models—specifically CNN, ResNet-50V2, and InceptionV3—for automated eye disease classification. Among the models evaluated, ResNet-50V2 and InceptionV3, both pre-trained on ImageNet, achieved superior performance over the custom CNN, benefiting from deeper architectures and transfer learning. ResNet-50V2 showed strong generalization due to its residual connections, while InceptionV3 effectively captured multi-scale features. These results highlight the potential of deep convolutional networks to assist ophthalmologists in early diagnosis and screening of eye diseases, thereby improving clinical outcomes and reducing diagnostic workload. Future work may focus on model interpretability, integration with clinical systems, and evaluation on more diverse datasets.

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