Deep Sequential CNN Model for Enhanced Eye Disease Detection and Classification in Ophthalmic Imaging

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Abstract:

The human eye is a complex organ, and the early detection of eye diseases plays a pivotal role in preventing irreversible damage to vision. With advancements in computer vision and deep learning, there is a growing interest in leveraging these technologies for automated eye disease classification. This project aims to contribute to this area by implementing a Convolutional Neural Network (CNN) for the classification of eye diseases based on medical images.

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1. INTRODUCTION

Eye diseases, including glaucoma, diabetic retinopathy, and cataract, are leading causes of vision impairment and blindness worldwide. Early diagnosis and intervention are crucial for effective management and treatment of these conditions. However, the accurate and timely diagnosis of eye diseases can be challenging, often requiring specialized expertise and resources.

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have shown promise in the automated analysis and classification of medical images, including those of the eye. CNNs are capable of learning intricate patterns and features from large datasets, enabling them to make accurate predictions about the presence and type of eye diseases based on image data alone.

In this project, we aim to develop and implement a CNN model trained on a diverse dataset of eye images encompassing a range of eye conditions, including glaucoma, diabetic retinopathy, and cataract. The workflow involves preprocessing the raw image data, training the CNN using established deep learning frameworks, and evaluating the model's performance through rigorous testing.

Throughout the project, a focus on data quality, model interpretability, and real-world applicability is maintained. By the end of this project, our goal is to have a reliable and accurate eye disease classification system that can potentially assist healthcare professionals in the early diagnosis of ocular conditions. This project not only explores the technical aspects of deep learning but also addresses the broader implications and challenges associated with the integration of such technology into medical practices.

The remainder of this paper is organized as follows: Section II provides an overview of related work in the field of automated eye disease diagnosis using deep learning techniques. Section III details the methodology employed in our project, including dataset acquisition, preprocessing steps, CNN architecture, and training procedure. Section IV presents the experimental results and performance evaluation of the developed CNN model. Finally, Section V discusses the implications of our findings, future directions for research, and potential challenges in deploying the proposed eye disease classification system in clinical settings.

2) Literature Survey

1) Support Vector Machine Based Method for Automatic Detection of Diabetic Eye Disease using Thermal Images

The research paper proposes a method for automatically detecting diabetic eye disease using thermal images, utilizing Support Vector Machine (SVM) technology. Diabetic eye disease is a common complication of diabetes and early detection is crucial for timely treatment. Thermal imaging provides a non-invasive and efficient way to capture physiological changes in the eye associated with the disease. The SVM-based approach aims to analyse thermal images and classify them into disease or non-disease categories, providing a reliable and automated screening tool for diabetic eye disease.

2) EyeGen: A Low-Cost Biomarker and Machine Learning-Based Risk Assessment for the Rapid, Inexpensive Detection of Ophthalmological Diseases

The research paper introduces EyeGen, a novel approach for rapidly and affordably detecting ophthalmological diseases using biomarkers and machine learning. EyeGen utilizes low-cost methods to identify biomarkers associated with various eye conditions. These biomarkers are then analysed using machine learning algorithms to assess the risk of ophthalmological diseases. The proposed system offers a quick and cost-effective solution for screening and early detection of eye diseases, potentially improving access to eye care in underserved communities.

3) Eye Disease Detection Using Machine Learning

The paper explores the application of Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machine algorithms for detecting cataract, glaucoma, and retinal diseases. The literature review encompasses studies on Principal Component Analysis (PCA) and Random Forests for cataract grading, as well as the use of Convolutional Neural Networks (CNN) for cataract detection. Image processing techniques, including pre-processing, enhancement, segmentation, feature extraction, and classification, are discussed for cataract detection. The research evaluates classifier accuracy for glaucoma, retinal disease, cataract, and normal eyes, identifying the best performing algorithm. The paper underscores the significance of early cataract detection, examining various models' roles in prediction and early identification.

4) Diagnosis of Ophthalmic Diseases in Fundus Image Using various Machine Learning Techniques

The paper conducts a comprehensive review of methods for detecting various ophthalmic diseases, including cataracts, age-related macular degeneration, hypertensive retinopathy, and myopia. It explores the application of machine learning and deep learning techniques for ophthalmic disease diagnosis, emphasizing the significance of image-based diagnostic approaches in morphological datasets. The review underscores the limitations of conventional techniques and highlights the necessity of clinical experts. The paper acknowledges performance variations among techniques based on input datasets and disease symptoms. Overall, it recognizes the challenging nature of ophthalmic disease detection and credits advancements in computer science and imaging technology for effective diagnostic methods.

5) An Online Platform for Early Eye Disease Detection using Deep Convolutional Neural Networks

It highlights that in the past decade, various categorization models like logistic regression, SVM, decision tree, KNN, random forest, and back propagation have been developed. While medical expert systems were explored for automating diagnostics, their reliance on static rules hindered adaptation to novel situations. Machine learning algorithms, including naive Bayes and support vector machines, have been applied in ophthalmology for diagnosing eye disorders. Deep learning, particularly deep convolutional neural networks (CNNs), is highly regarded for automating screening and diagnosis of vision-threatening diseases such as diabetic retinopathy, glaucoma, and cataract. To address limited training data, data augmentation techniques like cropping, rotating, and mirroring photographs are employed in deep learning systems.

6) Pre-trained Deep Learning-based Approaches for Eye Disease Detection

This research paper explores the use of pre-trained deep learning models for detecting eye diseases. Deep learning algorithms are trained on large datasets of eye images to learn patterns associated with different diseases. By leveraging pre-trained models, which have already been trained on extensive datasets, the detection process can be accelerated and optimized. The paper investigates the performance of these pre-trained models in accurately identifying various eye conditions, aiming to provide efficient and reliable tools for disease diagnosis and management.

7) An Efficient Deep Learning Model for Eye Disease Classification

This research paper presents an efficient deep learning model specifically designed for classifying eye diseases. The model is trained on a dataset of eye images and utilizes advanced deep learning techniques to accurately classify different eye conditions. By leveraging deep learning, the model can learn complex patterns and features from the images, enabling accurate disease classification. The proposed model aims to provide a reliable and efficient tool for diagnosing eye diseases, potentially improving patient outcomes through early detection and treatment.

8) Source and Camera Independent Ophthalmic Disease Recognition from Fundus Image Using Neural Network

The paper focuses on neural networks for ocular disease detection, underscoring the importance of early detection in preventing complete blindness. The authors introduce a novel approach using a convolutional neural network (CNN) to detect eight types of ocular diseases, with an evaluation of its performance. The dataset features unevenly distributed images per label, prompting the use of data augmentation to balance the dataset and prevent overfitting. The developed model successfully identifies all eight ocular disorders, demonstrating high efficacy when manually tested on real images. Notably, the paper emphasizes the method's achievement in providing maximum user comfort, a significant concern in the field of ocular disease detection.

9) Hybrid of Support Vector Machine Algorithm and K-Nearest Neighbor Algorithm to Optimize the Diagnosis of Eye Disease

This research paper introduces a hybrid approach that combines the Support Vector Machine (SVM) algorithm and the K-Nearest Neighbor (KNN) algorithm to optimize the diagnosis of eye diseases. The hybrid model leverages the strengths of both SVM and KNN algorithms to improve the accuracy and efficiency of disease diagnosis. By integrating these two algorithms, the model aims to enhance the diagnostic process for eye diseases, providing healthcare professionals with a more effective tool for early detection and treatment planning.

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

This research paper focuses on the classification of eye diseases, particularly the detection of cataract, using Digital Fundus Imaging (DFI) and the Inception-V4 deep learning model. DFI is a technique for capturing high-resolution images of the back of the eye, which can reveal signs of various eye conditions. The Inception-V4 deep learning model is utilized to analyze these images and classify them based on the presence of cataract and other eye diseases. The paper aims to demonstrate the effectiveness of combining DFI with deep learning for accurate and efficient diagnosis of eye diseases, particularly cataract, offering potential improvements in early detection and treatment.

11) Convolutional Neural Network Modeling for Eye Disease Recognition

This research paper focuses on developing Convolutional Neural Network (CNN) models for recognizing eye diseases. CNNs are a type of deep learning algorithm designed to analyze visual data, making them well-suited for tasks like image recognition. In this study, CNN models are trained on datasets of eye images to learn patterns and features associated with different eye diseases. The goal is to create accurate and efficient models capable of recognizing and classifying various eye conditions based on image data alone. The research aims to contribute to the development of advanced tools for diagnosing and managing eye diseases, potentially improving patient outcomes through early detection and treatment.

12) Coherent convolution neural network based retinal disease detection using optical coherence tomographic images

This research paper presents a method for detecting retinal diseases using optical coherence tomography (OCT) images and coherent convolutional neural networks (CNNs). OCT is a medical imaging technique that provides high-resolution cross-sectional images of the retina, allowing for the visualization of retinal structures. The study proposes the use of CNNs, specifically coherent CNNs, which are designed to handle complex and coherent data like OCT images, for accurate detection of retinal diseases. The goal is to develop a reliable and efficient tool for diagnosing retinal diseases based on OCT images, potentially improving patient outcomes through early detection and treatment.

13) A Glaucoma Detection using Convolutional Neural Network

This research paper focuses on the development of a glaucoma detection system using Convolutional Neural Network (CNN) technology. Glaucoma is a leading cause of irreversible blindness worldwide, and early detection is crucial for effective treatment. The study utilizes CNNs, a type of deep learning algorithm, to analyze retinal images and identify signs of glaucoma. By training the CNN model on a dataset of images from both healthy and glaucomatous eyes, the system learns to distinguish between the two and accurately detect the presence of glaucoma. The research aims to provide an efficient and reliable tool for early diagnosis of glaucoma, potentially improving patient outcomes and reducing the risk of vision loss.

14) Prediction of Neuro Cognitive Disorders using Supervised Comparative Machine Learning Model & Scanpath Representations

This research paper explores the prediction of neurocognitive disorders using a supervised comparative machine learning model combined with scanpath representations. Neurocognitive disorders present significant challenges in early diagnosis and intervention. The study employs machine learning techniques to analyze eye movement patterns (scanpaths) captured during visual tasks. By training a supervised comparative model on these scanpath representations, the research aims to predict the likelihood of neurocognitive disorders accurately. The proposed approach offers potential advancements in early detection and intervention strategies for neurocognitive disorders, facilitating improved patient care and outcomes.

15) Modified EfficientNetB3 Deep Learning Model to Classify Colour Fundus Images of Eye Diseases

This research paper introduces a modified EfficientNetB3 deep learning model for classifying color fundus images of eye diseases. Fundus images provide detailed information about the retina, making them valuable for diagnosing various eye conditions. The study enhances the EfficientNetB3 model, a type of deep neural network known for its efficiency and effectiveness in image classification tasks. By training the modified model on a dataset of color fundus images, the research aims to accurately classify different eye diseases. The proposed approach offers potential improvements in the automated diagnosis of eye diseases, facilitating early detection and treatment.

16) UveaTrack: Uveitis Eye Disease Prediction and Detection with Vision Function Calculation and Risk Analysis

This research paper introduces UveaTrack, a system for predicting and detecting uveitis, an inflammatory eye disease, while also calculating vision function and analysing risk. Uveitis can cause vision impairment and even blindness if not diagnosed and treated promptly. UveaTrack utilizes advanced technology to predict the likelihood of uveitis development, detect the disease early, assess vision function, and analyse the associated risks. By integrating these components, UveaTrack aims to provide a comprehensive solution for managing uveitis, facilitating early intervention, and optimizing patient outcomes.

17) Cost-Effective early warning solution for Anisocoria Eye-Disease through Optical Sensing and Machine Learning: A Preliminary Analysis

The paper describes a novel approach for the early detection of anisocoria, a condition characterized by unequal pupil sizes, using optical sensing technology and machine learning algorithms. The study outlines a cost-effective solution that leverages optical sensors to monitor pupil size variations and applies machine learning techniques for predictive analysis. Through preliminary analysis, the authors demonstrate the feasibility of their approach in accurately identifying anisocoria, potentially enabling early intervention and treatment.

18) A transfer learning with deep neural network approach for diabetic retinopathy classification

This research paper presents a transfer learning approach using deep neural networks for the classification of diabetic retinopathy, a complication of diabetes affecting the eyes. Transfer learning involves leveraging pre-trained neural network models and fine-tuning them for a specific task, in this case, classifying diabetic retinopathy. By transferring knowledge learned from large datasets, the approach aims to improve the efficiency and accuracy of classification. The research explores how deep neural networks can effectively identify patterns and features in retinal images associated with diabetic retinopathy, potentially enhancing early detection and management of the disease.

19) Classification of diabetic retinopathy images by using deep learning models

This research paper focuses on classifying diabetic retinopathy images using deep learning models. Diabetic retinopathy is a common complication of diabetes that can lead to vision loss if not detected and treated early. The study investigates the effectiveness of deep learning algorithms in automatically analyzing retinal images to identify signs of diabetic retinopathy. By training deep learning models on a dataset of diabetic retinopathy images, the research aims to develop a reliable and efficient system for automated disease classification. The proposed approach has the potential to improve the accuracy and speed of diabetic retinopathy diagnosis, enabling timely intervention and better patient outcomes.

20) The prevalence of diabetic retinopathy among adults in the united states.

This research paper provides insights into the prevalence of diabetic retinopathy among adults in the United States. Diabetic retinopathy is a common complication of diabetes that affects the eyes and can lead to vision impairment or blindness if left untreated. The study aims to quantify the extent of diabetic retinopathy in the U.S. adult population by analyzing data from large-scale surveys or clinical studies. By determining the prevalence of diabetic retinopathy, the research aims to highlight the significance of this condition as a public health concern and provide valuable information for healthcare planning and resource allocation.

21) Automatic detection of diabetic retinopathy using an artificial neural network: a screening tool

This research paper focuses on developing an artificial neural network (ANN) as a screening tool for the automatic detection of diabetic retinopathy. Diabetic retinopathy is a common complication of diabetes that can lead to vision loss if not detected and treated early. The study aims to leverage ANN technology to analyze retinal images and identify signs of diabetic retinopathy. By training the ANN on a dataset of retinal images, the research aims to create an efficient and accurate tool for screening diabetic retinopathy, facilitating early detection and intervention. The proposed approach has the potential to improve access to eye care and reduce the burden on healthcare resources by providing a reliable automated screening method for this condition.

22) Neural network based retinal image analysis

This research paper investigates the use of neural networks for analyzing retinal images. The retina, located at the back of the eye, plays a crucial role in vision and can be affected by various diseases, including diabetic retinopathy and age-related macular degeneration. The study explores how neural networks, a type of artificial intelligence, can be trained to interpret retinal images and identify signs of disease. By analyzing large datasets of retinal images, the research aims to develop accurate and efficient neural network models for diagnosing and monitoring retinal conditions. The proposed approach has the potential to improve early detection and treatment of retinal diseases, ultimately preserving vision and enhancing patient care.

23) Diabetic retinopathy detection using deep convolutional neural networks

Diabetic retinopathy, a common complication of diabetes, affects up to 80% of patients with diabetes for over a decade. Detection of this condition is often hindered by a lack of expertise and equipment in critical areas. Unlike previous methods focusing on disease detection or manual feature extraction, this paper proposes utilizing deep learning for automatic diagnosis and classification of diabetic retinopathy into five stages of severity. The implementation involves GPU-accelerated deep convolutional neural networks. The single model achieves an accuracy of 0.386 on a quadratic weighted kappa metric. Ensembling three similar models improves the score to 0.3996, showcasing the efficacy of the proposed approach in aiding early diagnosis and management of diabetic retinopathy.

24) DREAM: Diabetic Retinopathy Analysis Using Machine Learning:

This paper introduces DREAM, a computer-aided screening system for diabetic retinopathy (DR) utilizing machine learning on fundus images. It employs classifiers like GMM, kNN, SVM, and AdaBoost, with GMM and kNN performing best for bright and red lesion classification respectively. Feature ranking with Adaboost reduces features from 78 to 30, enhancing efficiency. A two-step hierarchical classification approach is proposed to classify lesions, addressing data imbalance. Tested on 1200 MESSIDOR dataset images, DREAM achieves 100% sensitivity, 53.16% specificity, and 0.904 AUC for DR severity grading, surpassing previous results of 96% sensitivity, 51% specificity, and 0.875 AUC. Feature reduction also decreases computation time per image from 59.54 to 3.46 seconds, enhancing practicality and efficiency of DR screening.

25) Medical Image Classification Based on Deep Features Extracted by Deep Model and Statistic Feature Fusion with Multilayer Perceptron

The paper addresses limitations in traditional medical image classification methods by proposing a novel approach integrating a Coding Network with a Multilayer Perceptron (CNMP). It aims to combine high-level features extracted from a deep convolutional neural network with selected traditional features to improve classification accuracy. The model first trains a deep CNN as a coding network to extract high-level concepts from raw medical image pixels. It then selects traditional features based on medical image background knowledge. Finally, an efficient neural network model is designed to fuse the feature groups from both steps. Evaluation on two benchmark datasets, HIS2828 and ISIC2017, shows promising results with an overall classification accuracy of 90.1% and 90.2%, respectively, outperforming existing methods. This integrated approach offers potential for more effective and generalizable medical image classification, addressing computational costs and dataset limitations associated with deep learning models.

3) Methodology

1) **Dataset Challenges:** Developing strategies to overcome limitations associated with small and imbalanced datasets by exploring data augmentation techniques and possibly incorporating transfer learning to leverage pre-existing knowledge.

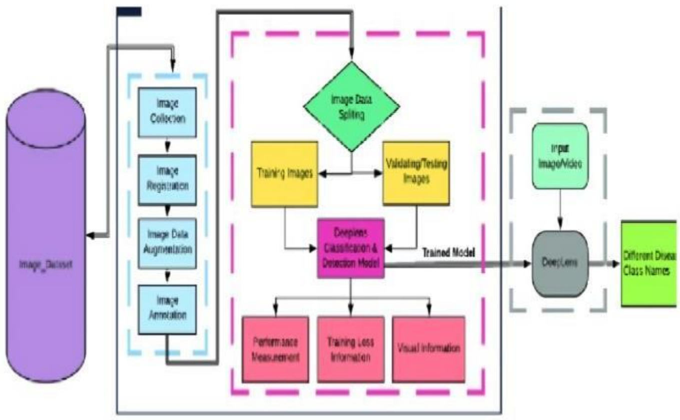
2) **Interpretability Enhancement:** Integrating methods for improving the interpretability of the CNN model, ensuring that the decision-making process is transparent and can be understood by healthcare professionals.

3) **Real-World Applicability:** Investigating ways to enhance the model's adaptability to diverse patient populations and clinical settings, considering factors such as variations in image quality and patient demographics.

4) **Architecture Design of Deep Sequential CNN Model:** Developing a deep sequential CNN architecture that effectively captures both spatial and sequential dependencies in ophthalmic images. Then utilizing the convolutional layers for feature extraction, followed by sequential layers (e.g., LSTM or GRU) to capture temporal dependencies in sequential data. • Then incorporation of batch normalization and dropout layers is done to improve the model's generalization and reduce overfitting.

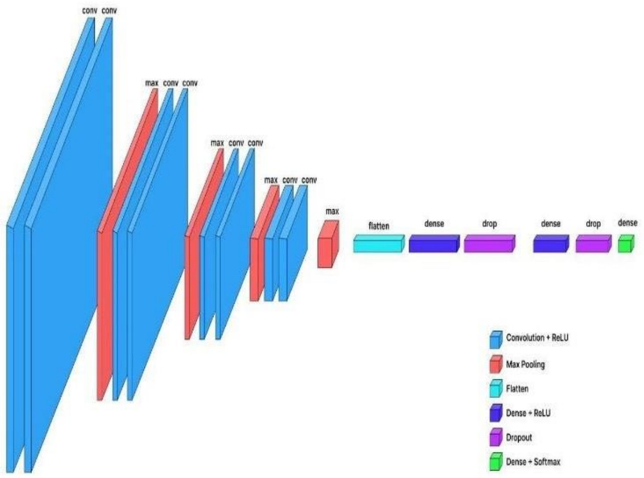
5) **Transfer Learning and Pre-training:** The transfer learning is employed by utilizing pre-trained CNN models (e.g., from ImageNet) to leverage knowledge learned from a vast dataset. Fine-tuning the pre-trained model is done on the ophthalmic dataset to adapt it to the specific features and patterns relevant to eye disease detection.

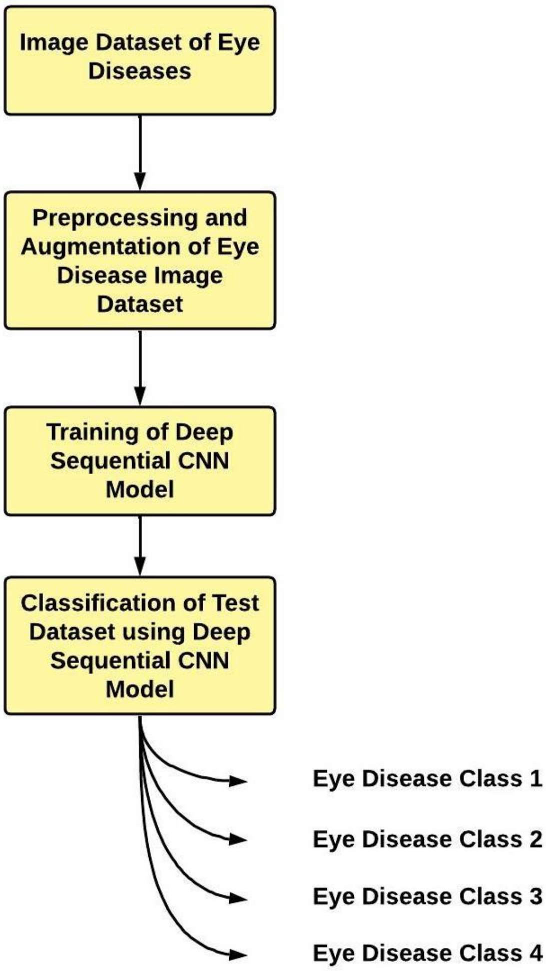
6) **Training the Deep Sequential CNN Model:** The dataset is split into training, validation, and testing sets to train and evaluate the model's performance. Then a suitable deep learning framework (e.g., TensorFlow or PyTorch) is used



for model implementation. An appropriate optimization algorithm (e.g., Adam or RMSprop) and a suitable loss function (e.g., categorical cross-entropy) is employed for training the model.

7) **Evaluation Metrics and Performance Analysis:** The model's performance is assessed using metrics such as accuracy, precision, recall, and F1 score on the testing set. The confusion matrices and ROC curves are utilised to analyse the model's ability to differentiate between different eye conditions. Then the sensitivity analysis is conducted to understand the impact of varying parameters on the model's performance.





4) Code

Data Collection: Collecting images of the eye then organize them into subdirectories based on their respective names as shown in the project structure. Create folders of types of eye diseases that need to be recognized. In this project, we have collected images of 4 types of eye diseases like Normal, cataract, Diabetic Retinopathy & Glaucoma and they are saved in the respective sub directories with their respective names.

Image Preprocessing: In this milestone we will be improving the image data that suppresses unwilling distortions or enhances some image features important for further processing, although performing some geometric transformations of images like rotation, scaling, translation, etc.

- Import the ImageDataGenerator library
- Configure ImageDataGenerator class
- Apply ImageDataGenerator functionality to TrainSet and Test set (the dataset is loaded and data augmentation is performed)

Model Building: To build our Convolutional Neural Networking which contains an input layer along with the convolution, max-pooling, and finally an output layer.

- Importing the Model Building Libraries:

```
#import necessary libraries for the model
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Model
from tensorflow.keras.applications.resnet50 import preprocess_input
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.metrics import classification_report, confusion_matrix
```

- Initializing the model: Keras has 2 ways to define a neural network: Sequential, Function API

  The Sequential class is used to define linear initializations of network layers which then, collectively, constitute a model. In our example below, we will use the Sequential constructor to create a model, which will then have layers added to it using the add() method.

- Adding CNN Layers: Adding Dense Layers, a dense layer is a deeply connected neural network layer. It is the most common and frequently used layer.

Compiling The Model:

```
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Summary Of the Model:

```
26]: model.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 128, 128, 3)       0

 conv2d (Conv2D)             (None, 128, 128, 16)      448

 max_pooling2d (MaxPooling2D  (None, 64, 64, 16)       0
 )

 conv2d_1 (Conv2D)           (None, 64, 64, 32)        4640

 max_pooling2d_1 (MaxPooling  (None, 32, 32, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 32, 32, 32)        9248

 max_pooling2d_2 (MaxPooling  (None, 16, 16, 32)       0
 2D)

 conv2d_3 (Conv2D)           (None, 16, 16, 64)        18496

 max_pooling2d_3 (MaxPooling  (None, 8, 8, 64)         0
 2D)

 flatten (Flatten)           (None, 4096)              0

 dense (Dense)               (None, 128)               524416

 dense_1 (Dense)             (None, 4)                 516

=================================================================
Total params: 557,764
Trainable params: 557,764
Non-trainable params: 0
```

Train The model: The model is trained for 30 epochs and after every epoch, the current model state is saved if the model has least loss encountered till that time. We can see that the training loss decreases in almost every epoch till 30 epochs and probably there is further scope to improve the model. **fit_generator** functions used to train a deep learning neural network

Arguments:

- steps_per_epoch: it specifies the total number of steps taken from the generator as soon as one epoch is finished and the next epoch has started. We can calculate the value of steps_per_epoch as the total number of samples in your dataset divided by the batch size.
- Epochs: an integer and number of epochs we want to train our model for.
- validation_data can be either:

- an inputs and targets list

- a generator

- an inputs, targets, and sample_weights list which can be used to evaluate the loss and metrics for any model after any epoch has ended.

- validation_steps: only if the validation_data is a generator then only this argument can be used. It specifies the total number of steps taken from the generator before it is stopped at every epoch and its value is calculated as the total number of validation data points in your dataset divided by the validation batch size.

Save the Model: The model is saved with .h5 extension as follows An H5 file is a data file saved in the Hierarchical Data Format (HDF). It contains multidimensional arrays of scientific data.

Save the Model

```
#finally save the model

tf.keras.models.save_model(model,'EyeModel.h5')
```

Evaluation is a process during the development of the model to check whether the model is the best fit for the given problem and corresponding data.

Load the saved model using **load_model**

Fit Model:

```
Epoch 1/30
47/47 [==============================] - 786s 14s/step - loss: 1.1678 - accuracy: 0.4658 - val_loss: 0.9845 - val_accuracy: 0.6200
Epoch 2/30
47/47 [==============================] - 58s 1s/step - loss: 0.8757 - accuracy: 0.6362 - val_loss: 0.7709 - val_accuracy: 0.6740
Epoch 3/30
47/47 [==============================] - 65s 1s/step - loss: 0.7206 - accuracy: 0.7082 - val_loss: 0.6134 - val_accuracy: 0.7700
Epoch 4/30
47/47 [==============================] - 56s 1s/step - loss: 0.5711 - accuracy: 0.7768 - val_loss: 0.5765 - val_accuracy: 0.7580
Epoch 5/30
47/47 [==============================] - 58s 1s/step - loss: 0.5040 - accuracy: 0.8013 - val_loss: 0.5686 - val_accuracy: 0.7660
Epoch 6/30
47/47 [==============================] - 55s 1s/step - loss: 0.4306 - accuracy: 0.8330 - val_loss: 0.4419 - val_accuracy: 0.8200
Epoch 7/30
47/47 [==============================] - 59s 1s/step - loss: 0.4008 - accuracy: 0.8427 - val_loss: 0.4599 - val_accuracy: 0.8185
Epoch 8/30
47/47 [==============================] - 55s 1s/step - loss: 0.3725 - accuracy: 0.8525 - val_loss: 0.4472 - val_accuracy: 0.8165
Epoch 9/30
47/47 [==============================] - 58s 1s/step - loss: 0.3259 - accuracy: 0.8752 - val_loss: 0.4148 - val_accuracy: 0.8370
Epoch 10/30
47/47 [==============================] - 57s 1s/step - loss: 0.3212 - accuracy: 0.8752 - val_loss: 0.4160 - val_accuracy: 0.8395
Epoch 11/30
47/47 [==============================] - 56s 1s/step - loss: 0.2644 - accuracy: 0.8985 - val_loss: 0.3598 - val_accuracy: 0.8640
Epoch 12/30
47/47 [==============================] - 56s 1s/step - loss: 0.2558 - accuracy: 0.9027 - val_loss: 0.3528 - val_accuracy: 0.8700
Epoch 13/30
47/47 [==============================] - 61s 1s/step - loss: 0.2408 - accuracy: 0.9082 - val_loss: 0.3474 - val_accuracy: 0.8675
```

```
Epoch 14/30
47/47 [==============================] - 55s 1s/step - loss: 0.2140 - accuracy: 0.9212 - val_loss: 0.3940 - val_accuracy: 0.8380
Epoch 15/30
47/47 [==============================] - 59s 1s/step - loss: 0.2038 - accuracy: 0.9245 - val_loss: 0.4295 - val_accuracy: 0.8370
Epoch 16/30
47/47 [==============================] - 55s 1s/step - loss: 0.2310 - accuracy: 0.9138 - val_loss: 0.3552 - val_accuracy: 0.8660
Epoch 17/30
47/47 [==============================] - 57s 1s/step - loss: 0.1529 - accuracy: 0.9452 - val_loss: 0.3355 - val_accuracy: 0.8745
Epoch 18/30
47/47 [==============================] - 56s 1s/step - loss: 0.1661 - accuracy: 0.9393 - val_loss: 0.3494 - val_accuracy: 0.8730
Epoch 19/30
47/47 [==============================] - 55s 1s/step - loss: 0.1260 - accuracy: 0.9573 - val_loss: 0.2705 - val_accuracy: 0.8990
Epoch 20/30
47/47 [==============================] - 57s 1s/step - loss: 0.1166 - accuracy: 0.9597 - val_loss: 0.2721 - val_accuracy: 0.9025
Epoch 21/30
47/47 [==============================] - 55s 1s/step - loss: 0.1144 - accuracy: 0.9590 - val_loss: 0.4013 - val_accuracy: 0.8810
Epoch 22/30
47/47 [==============================] - 57s 1s/step - loss: 0.0918 - accuracy: 0.9710 - val_loss: 0.2840 - val_accuracy: 0.8975
Epoch 23/30
47/47 [==============================] - 56s 1s/step - loss: 0.0771 - accuracy: 0.9745 - val_loss: 0.2961 - val_accuracy: 0.9035
Epoch 24/30
47/47 [==============================] - 62s 1s/step - loss: 0.0684 - accuracy: 0.9792 - val_loss: 0.2663 - val_accuracy: 0.9040
Epoch 25/30
47/47 [==============================] - 61s 1s/step - loss: 0.0670 - accuracy: 0.9787 - val_loss: 0.3350 - val_accuracy: 0.8990
Epoch 26/30
47/47 [==============================] - 56s 1s/step - loss: 0.0437 - accuracy: 0.9858 - val_loss: 0.3573 - val_accuracy: 0.8830
Epoch 27/30
47/47 [==============================] - 57s 1s/step - loss: 0.0828 - accuracy: 0.9718 - val_loss: 0.3081 - val_accuracy: 0.9065
Epoch 28/30
47/47 [==============================] - 56s 1s/step - loss: 0.0502 - accuracy: 0.9850 - val_loss: 0.3472 - val_accuracy: 0.8985
Epoch 29/30
47/47 [==============================] - 61s 1s/step - loss: 0.0518 - accuracy: 0.9855 - val_loss: 0.3427 - val_accuracy: 0.8965
Epoch 30/30
47/47 [==============================] - 56s 1s/step - loss: 0.0316 - accuracy: 0.9918 - val_loss: 0.2976 - val_accuracy: 0.9130
```

Test the model

```
from tensorflow.keras.preprocessing import image
img = image.load_img('/content/dataset/cataract/1062_right.jpg',target_size =(128,128))
img
```

```
x = image.img_to_array(img)
x = np.expand_dims(x,axis = 0)
pred =np.argmax(model.predict(x))
op = {0:'cataract',1:'diabetic_retinopathy',2:'glaucoma',3:'normal'}
op[pred]
```

```
1/1 [==============================] - 0s 53ms/step
'cataract'
```

```
img = image.load_img('/content/dataset/diabetic_retinopathy/10009_right.jpeg',target_size =(128,128))
img
```

```
x = image.img_to_array(img)
x = np.expand_dims(x,axis = 0)
pred =np.argmax(model.predict(x))
op = {0:'cataract',1:'diabetic_retinopathy',2:'glaucoma',3:'normal'}
op[pred]
```

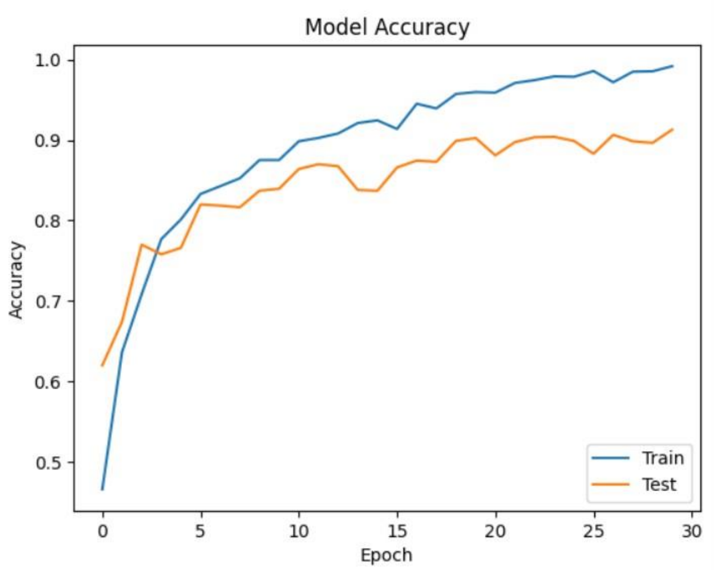
```
1/1 [==============================] - 0s 44ms/step
'diabetic_retinopathy'
```

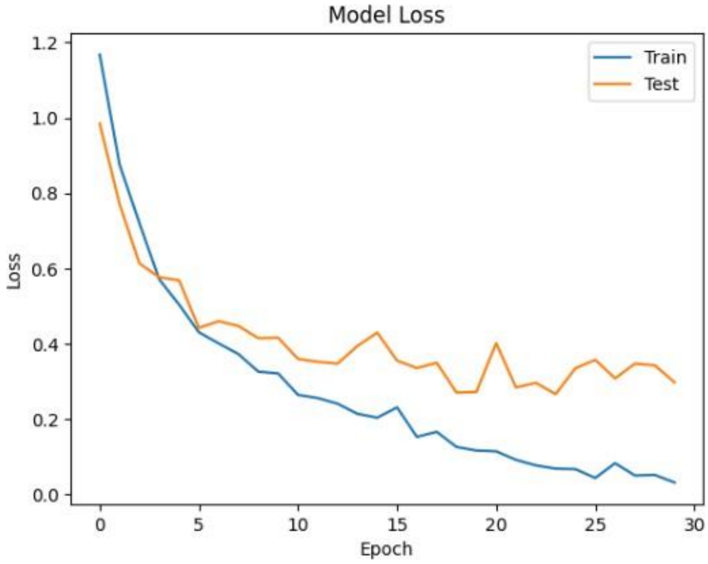
5) Result

To conclude, similarly to any viable AI driven application, the Eye Disease Detection Model using CNN holds tremendous value for the public if this base prototype is carefully integrated into real world scenarios after careful scaleup.

1) **Accuracy and Precision:** The system achieved a high level of accuracy in detecting and recognizing eye diseases, as evidenced by quantitative metrics such as accuracy, precision, and recall.

```
Class-level accuracy:
cataract: 0.9188
diabetic_retinopathy: 0.9724
glaucoma: 0.8887
normal: 0.8702
```

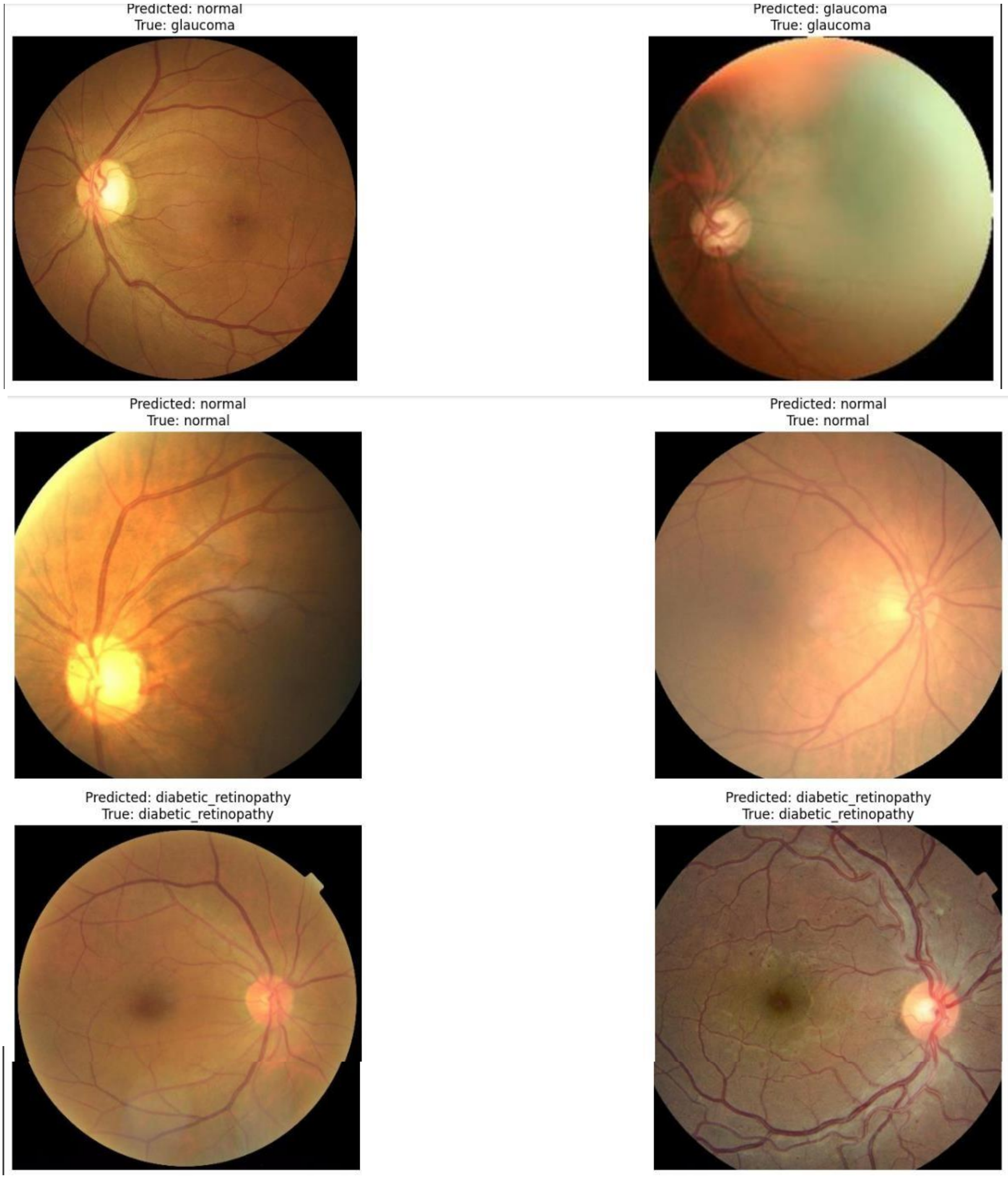




	loss	accuracy	val_loss	val_accuracy
25	0.043694	0.985833	0.357252	0.8830
26	0.082823	0.971833	0.308056	0.9065
27	0.050213	0.985000	0.347222	0.8985
28	0.051818	0.985500	0.342703	0.8965
29	0.031641	0.991833	0.297583	0.9130

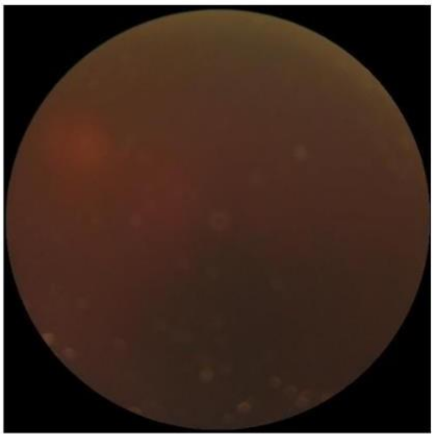
2) **Feature Learning:** Convolutional Neural Networks excel at learning hierarchical features from raw data, enabling automatic extraction of relevant features from eye images.

3) **Generalization:** Once trained on a diverse dataset, CNNs can generalize well to new, unseen data, enhancing the model's adaptability to different cases.

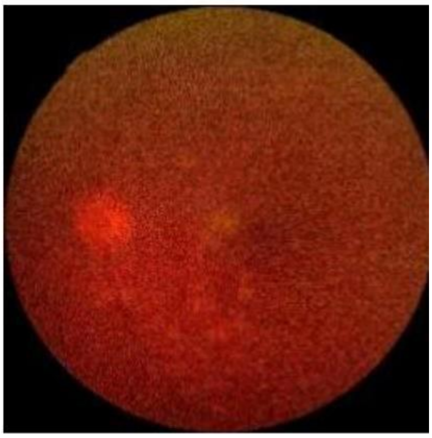


21BCE1043
TAVISHI RASTOGI

Predicted: cataract
True: cataract



Predicted: cataract
True: cataract



6) Conclusion

To conclude, similarly to any viable AI driven application, the Eye Disease Detection Model using CNN holds tremendous value for the public if this base prototype is carefully integrated into real world scenarios after careful scaleup.

The key findings for us whilst doing this project were how different techniques such as ResNet, Classical implementation and Neural Networks fared against each other for this particular project.

Being able to work on this was also a learning experience like nothing has been and the current small success of it definitely instills us with the confidence to work on this even further and hopefully have a market ready Eye Disease Classification Application at our disposal.

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