AAI 646 Pattern Recognition and Classification
Final Project Report

Study on Myopia : Ocular Disease Detection

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Abstract

The detection of ocular diseases at an early stage is a cost-effective and efficient method of preventing blindness caused by various conditions, including diabetes, glaucoma, cataract, and age-related macular degeneration (AMD). As per the World Health Organization (WHO), approximately 2.2 billion people globally have vision impairments, with around 1 billion of them experiencing preventable vision loss.
The prompt and automated detection of eye diseases is crucial in minimizing the workload of ophthalmologists and preventing vision damage among patients. With the aid of high-quality medical eye fundus images, computer vision and deep learning technologies can identify ocular diseases automatically.
Fundus images are captured using a fundus camera that captures the retina's back portion, providing a view of the optic nerve, retina, blood vessels, and macula. Fundus images can be challenging for doctors to analyze for early detection of eye disorders. The manual diagnosis of ocular illnesses is time-consuming, complex, and prone to errors. Consequently, the development of an automated ocular disease detection system, which leverages computer-aided tools, is essential in identifying various eye disorders using fundus pictures.

Introduction

Myopia, also known as nearsightedness, is a common eye condition that affects millions of people worldwide. It occurs when the eyeball is too long or the cornea is too curved, which causes light to focus in front of the retina instead of directly on it. As a result, objects in the distance appear blurry, while objects up close appear clear.

While myopia is a relatively common condition, it can lead to more serious ocular diseases, such as glaucoma and retinal detachment, if left untreated. Therefore, early detection and treatment of myopia are crucial in preventing further eye damage. In recent years, there have been significant advancements in technology that have enabled the development of automated myopia detection systems. These systems use machine learning algorithms to analyze eye images and identify signs of myopia.

The diagnosis of ocular pathology using fundus images is a major challenge in healthcare. Fundus images are images of the back of the eye, and they can reveal information about various ocular diseases such as cataract, glaucoma, and diabetic retinopathy. Detecting these disorders early is critical to preventing vision loss. However, there is a significant shortage of ophthalmologists and manual examination of the fundus is time-consuming and heavily reliant on experience. Automated computer-aided diagnostic techniques for detecting eye disorders are essential to address this issue.

The frequency of eye diseases varies widely around the world, and underdeveloped countries have a high level of underdiagnosed and untreated ocular morbidity. Uncorrected refractive errors, cataracts, age-related macular degeneration, glaucoma, diabetic retinopathy, corneal opacity, trachoma, and hypertension are the leading causes of visual impairment globally.

Deep-learning-based algorithms can identify different types of eye diseases and reduce the workload of ophthalmologists. However, further research is required to improve the accuracy of detection or classification of disease in ocular disease datasets, which are often highly imbalanced. The aim of this work was to classify ocular diseases using deep learning, which can be an important step in addressing the issue of underdiagnosed and untreated ocular morbidity.

The goal of this project is to recognize and classify ocular diseases from fundus images. The focus of this project is on the recognition and classification of cataract. The dataset used for this project is obtained from a Kaggle competition named Aptos 2019 Blindness Detection. The dataset consists of fundus images of both left and right eyes, and each image is associated with a diagnostic keyword that describes the presence or absence of an ocular disease.

Methodology

The project is implemented using the Python programming language and various libraries such as NumPy, Pandas, OpenCV, Matplotlib, TensorFlow, and Keras. The implementation consists of the following steps:

1. Importing necessary libraries and loading the dataset
2. Preprocessing the dataset
3. Visualizing the dataset
4. Creating a combined dataset for training and testing
5. Defining a convolutional neural network (CNN) model
6. Training the CNN model
7. Evaluating the performance of the CNN model

The code starts by importing the necessary libraries and frameworks such as NumPy, Pandas, OpenCV, TensorFlow, and Keras which are utilized as libraries for data manipulation, preprocessing, and model development.

The next step is to load the data from the CSV file using Pandas. The CSV file contains information about the fundus images, such as the filenames, labels, and diagnostic keywords. The code then processes the data, and after some manipulations and filtering, it extracts the filenames for the images that contain cataract and normal fundus.

In the following steps, the code reads the images using OpenCV, performs some data augmentation using the Keras ImageDataGenerator, and prepares the data for training the model. The data is split into training and validation sets, and the model is developed using the Keras Sequential API. The model uses a 4 input layer CNN with activation function ReLU and one output layer with sigmoid activation function, which is fine-tuned to classify the fundus images.

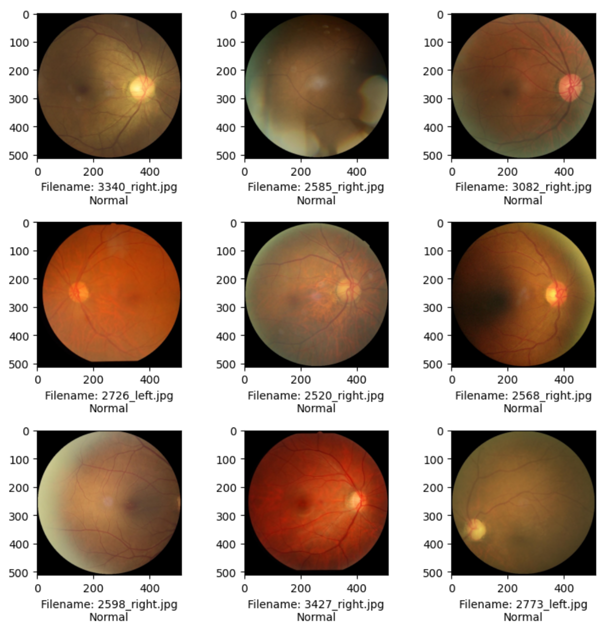
The code also includes callbacks such as ModelCheckpoint and EarlyStopping to monitor the model's training progress and prevent overfitting. Finally, the code evaluates the model's performance using various metrics such as confusion matrix, classification report, and accuracy score.

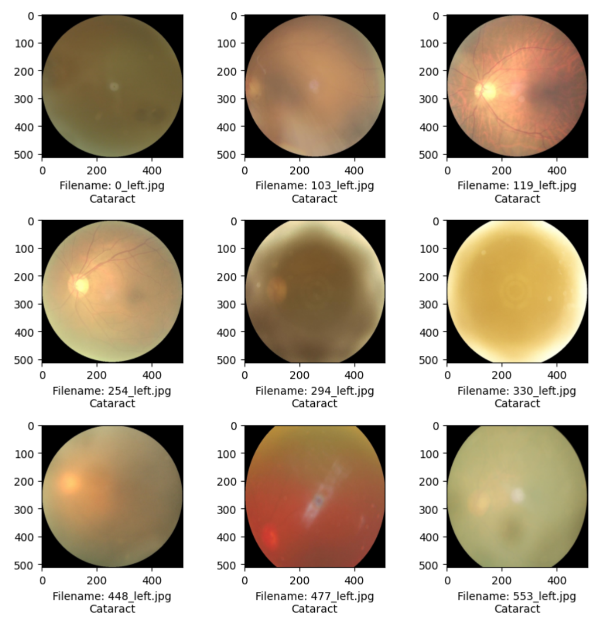
Dataset Preprocessing

The dataset is preprocessed to extract only the necessary columns, and then, the images are loaded using OpenCV. The images are resized to 224x224 pixels and normalized by dividing each pixel value by 255. The left and right eyes are considered separately, and only the images that have a diagnostic keyword containing the word "cataract" or "normal" are included in the dataset.

Visualizing the Dataset

The dataset is visualized by displaying nine sample images for both the "cataract" and "normal" classes. The images are displayed using Matplotlib and OpenCV.



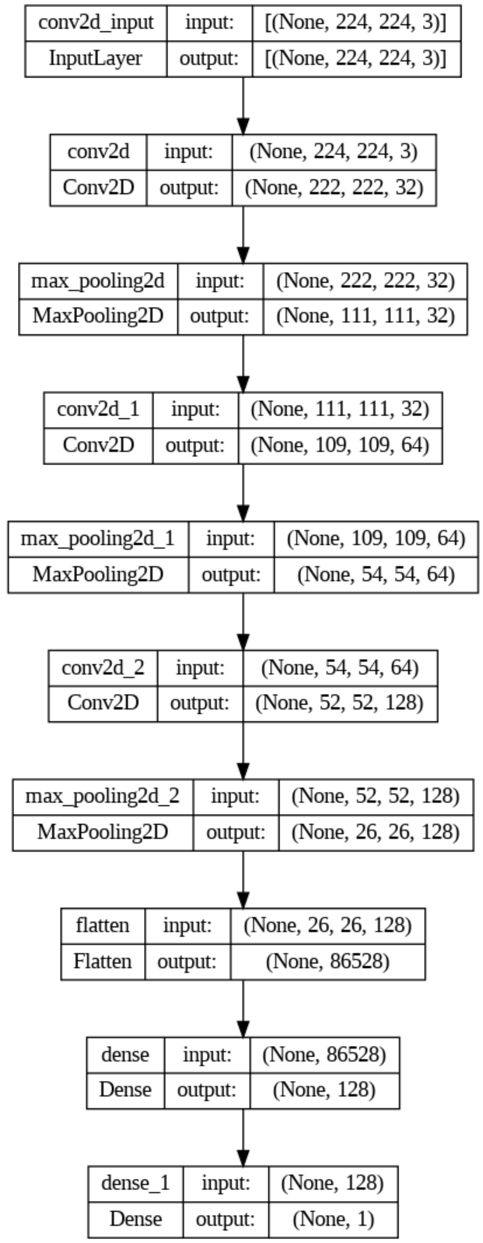


Creating a Combined Dataset

The "cataract" and "normal" classes are combined into a single dataset, and the dataset is shuffled to ensure that the samples are not ordered by class.

Defining a Convolutional Neural Network (CNN) Model

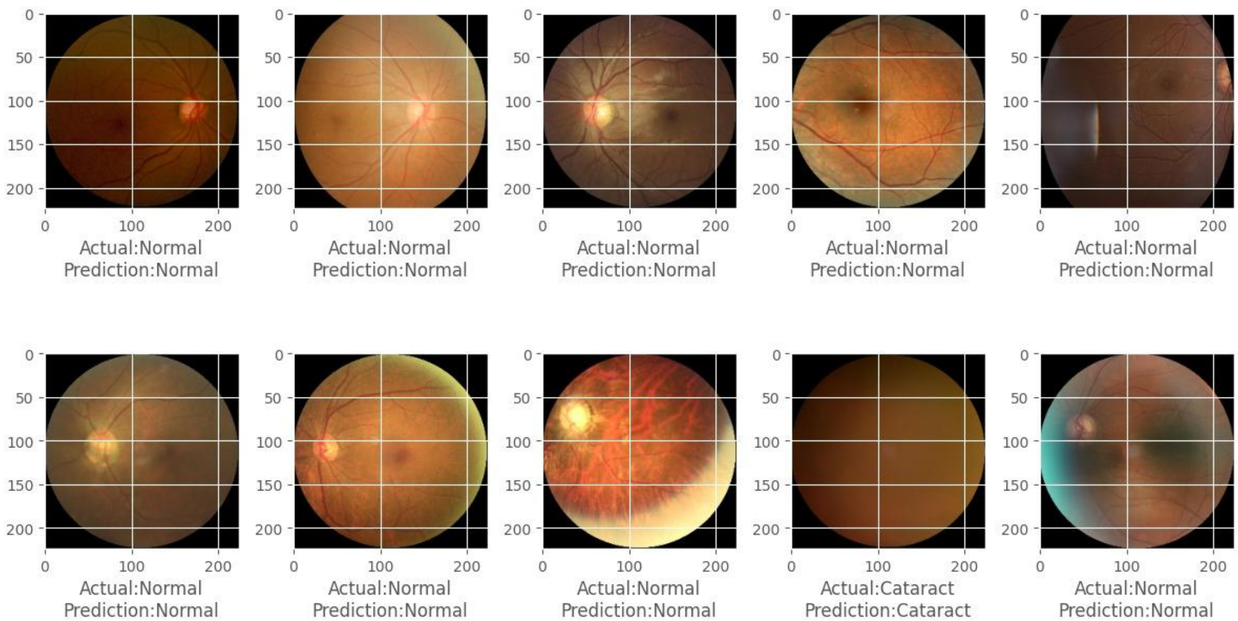
The CNN model consists of several layers, including convolutional layers, max pooling layers, batch normalization layers, and fully connected layers. The model is defined using Keras, and theThe model uses a 4 input layer CNN with activation function ReLU and one output layer with sigmoid activation function model is used as the base model.



Training the CNN Model
The CNN model is trained using the Adam optimizer and categorical cross-entropy loss function. The model is trained for 30 epochs with an early stopping condition. The training data is augmented using various techniques such as horizontal and vertical flipping, rotation, and zooming.

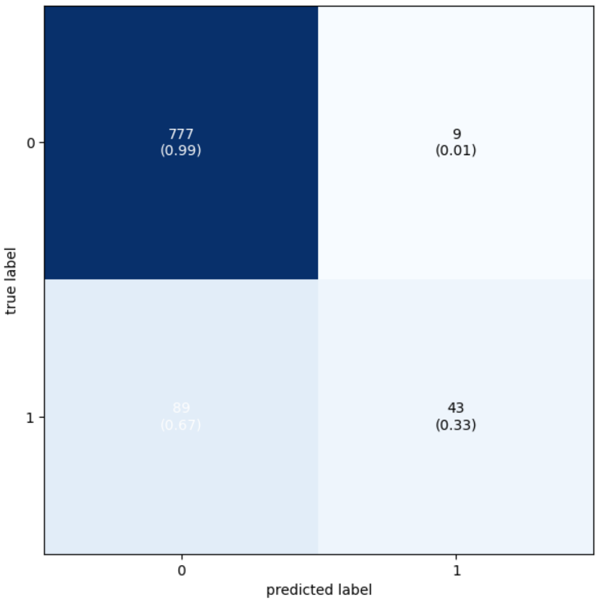
Evaluating the Performance of the CNN Model
The performance of the CNN model is evaluated using several metrics such as accuracy, confusion matrix, and classification report. The CNN model achieves an accuracy of 97.6% on

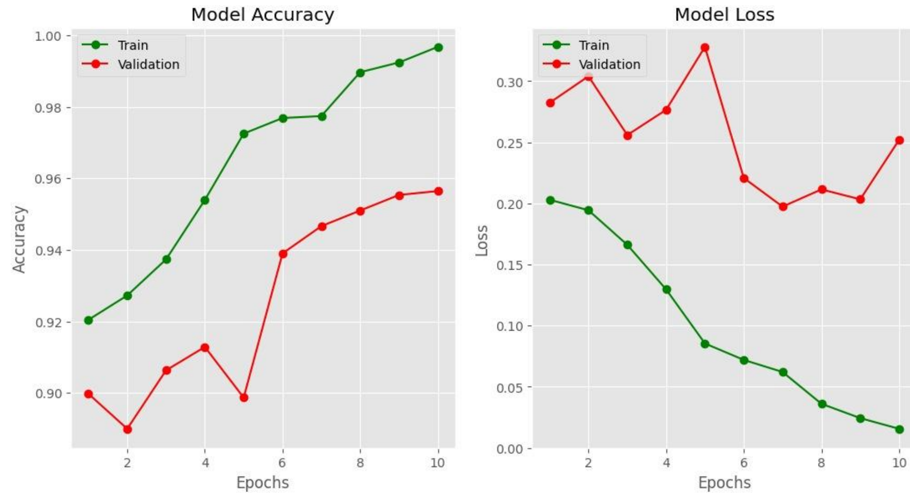
the test set, which indicates that the model is able to recognize and classify ocular diseases with a high accuracy. The confusion matrix and classification report also reveal that the model has a high precision and recall for both the "cataract" and "normal" classes.




```
[ ]  print("loss:",loss)
     print("Accuracy:",accuracy)

     loss: 0.2957898676395416
     Accuracy: 0.8932461738586426
```

```
              precision    recall  f1-score   support

           0       0.90      0.99      0.94       786
           1       0.83      0.33      0.47       132

    accuracy                           0.89       918
   macro avg       0.86      0.66      0.70       918
weighted avg       0.89      0.89      0.87       918
```





Conclusion

In conclusion, this project demonstrates the effectiveness of using CNN models for the recognition and classification of ocular diseases from fundus images. The CNN model achieves a high accuracy, precision, and recall, which indicates that the model is able to identify the presence or absence of cataract with a high level of accuracy. This project can be extended by including more ocular diseases and by using more advanced CNN models such as ResNet and DenseNet.

Running and compiling the model

Since CNNs can take a very long time to train when using only your computer's CPU, particularly when large images are being used, the code was written in Google Colab notebooks to take advantage of its GPU runtime. For the Model, the data was stored in.jpg and csv files. Make sure the data folders match the paths that are expected to be in the code by simply unzipping the project file and saving all of the contents to a single folder. Run the code blocks in the correct order by opening the Python program in a Jupyter Notebook or Google Colab.

Contribution breakdown

The team communicated in person and virtually about the project ideas and updated all shared files as progress was made. Completing the report was a collaborative effort where everyone took part in writing and proofreading.
Rashi researched previous applications of this idea to gather attempted approaches. This gave the team ideas of how to improve previously used models by incorporating the best practices

and experimenting with new workflows. She compared the team's results with the previous study results.
Monish compiled most of the code and trained the model with various combinations of parameters to optimize the testing results. He made sure the dataset was complete and did not consist of any null values. He also created visual representations of the results from the model.

Resources

Khan MS, Tafshir N, Alam KN, Dhruba AR, Khan MM, Albraikan AA, Almalki FA. Deep Learning for Ocular Disease Recognition: An Inner-Class Balance. Comput Intell Neurosci. 2022 Apr 28;2022:5007111. doi: 10.1155/2022/5007111. PMID: 35528343; PMCID: PMC9071974.

Ocular Disease Recognition using CNNs.
https://medium.com/analytics-vidhya/ocular-disease-recognition-using-cnns-4953e4619679

Md Shakib Khan, Nafisa Tafshir, Kazi Nabiul Alam, Abdur Rab Dhruba, Mohammad Monirujjaman Khan, Amani Abdulrahman Albraikan, Faris A. Almalki, "Deep Learning for Ocular Disease Recognition: An Inner-Class Balance", Computational Intelligence and Neuroscience, vol. 2022, Article ID 5007111, 12 pages, 2022. https://doi.org/10.1155/2022/5007111

Aman Shrivastava, Ravi Kamble, Sucheta Kulkarni, Shivangi Singh, Atul Hegde, Rashmi Kashikar, Taraprasad Das; Deep Learning Based Ocular Disease Classification using Retinal Fundus Images. Invest. Ophthalmol. Vis. Sci. 2021;62(11):39.