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Project Guide

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DEVELOPING AN ADVANCED FUNDUS CAMERA FOR OCULAR HEALTH ASSESSMENT

Submitted in partial fulfillment of the requirements of

PG-DIPLOMA IN BIG DATA ANALYTICS

By

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CERTIFICATE

This is to certify that the project entitled "**Developing an advanced fundus camera for ocular health assessment**" is a teamwork work of **"Rajesh Rane (230310125013), Akshay Hanumante (230310125007), Swapnil Randive (230310125014)."** Submitted to C-DAC New Delhi in partial fulfillment of the requirement for the PG-DBDA in Big Data Analytics.

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DECLARATION

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. We understand that any violation of the above will cause disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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ABSTRACT

Ocular health assessment is a critical component of preventive care. However, traditional methods of ocular health assessment, such as manual grading of fundus images, can be time-consuming and prone to errors. Machine learning (ML) has the potential to automate ocular health assessment and improve its accuracy. This study proposes the development of an ML model for ocular health assessment using an advanced fundus camera. The model will be trained on a dataset of fundus images with ground truth labels for various ocular health conditions. The model could also be used to improve the accuracy of ocular health assessment, which could lead to earlier detection and treatment of eye diseases.

Chapter 1
INTRODUCTION OF PROJECT

1.1 Introduction

Fundus diseases affect millions of people worldwide. They include diseases like diabetic retinopathy, age-related macular degeneration, cataract, glaucoma and hypertensive retinopathy, among others. India has a high prevalence rate of 16.9% for diabetic retinopathy (Vashist, 2021), and 12 million people suffer from glaucoma (George R, 2010).

An estimated 100 million people go blind from cataract and 8 million from age-related macular degeneration (ARMD) every year (Sen M, 2022). Machine learning-based tools can help ease the load on the healthcare sector by assisting in diagnosis to improve accessibility and, in some cases, the accuracy of the treatment method prescribed.

Deep learning-based techniques allow for an even greater level of flexibility in the diagnostic procedure, allowing for multimodal diagnosis and taking inputs from a variety of sources (Ngiam et al., 2011)

1.2 Scope

Main scope of this project is to Create a comprehensive and user-friendly model for detecting a wider range of eye diseases, including those that are not well-understood, and ensuring it is easy for clinicians to use and interpret the result

Chapter 2

DATASET DETAILS

The dataset was taken from the ODIR-2019 challenge by Peking University, China. The dataset instance used was taken from Kaggle (Larxel, 2021). The dataset has a main directory comprised of preprocessed images of dimension 512 x 512, in RGB color format. It also has two additional directories for the test-train split (pre-split), but we did not use that in our methods. There is an excel file having the dataset description Table 1.

Feature	**Description**
ID	Identifier
Age	Integer
Sex	Male or Female
Eye	Whether left or right eye
Keywords	Diagnostics keywords
Diagnostics column	Features: N (normal), G (glaucoma), D (diabetes), C (cataract), A (ARMD), M (Pathological Myopia), H (hypertension), O (others)

Table 1: Dataset description

Chapter 3

PROJECT METHODOLOGY

3.1 Dataset Manipulation

The dataset we're using has a significant class imbalance. For example, there are approximately 1140 images of normal Fundus, but only 174 samples for Myopia. To achieve our project's goal of classifying ocular diseases into four categories (normal, Cataract, Glaucoma, and Myopia), we created a mini dataset by extracting relevant images from the main dataset. This extraction was done using a Python script that identified images with diagnostic keywords, like 'cataract.' We then filtered images with the 'C' label (indicating Cataract) and repeated this process for Normal, Glaucoma, and Myopia classes. These filtered data frames were combined to create a sub-dataset.

The sub-dataset comprises approximately 600 images each for normal eye Fundus, cataract, glaucoma, and myopia. To enhance image details, we applied Contrast Limited Adaptive Histogram Equalization (CLAHE) based on previous research. We converted the images to the 'LAB color format' (L for Lightness, A for color component from Green to Magenta, B for color component from Blue to Yellow), and applied CLAHE to the L channel, resulting in the images. This processed dataset was split into training (60%), validation (30%), and test (10%) sets, comprising approximately 2020 images for model development and 225 images for testing.

3.2 VGG19 Model

About the VGG19 model (pre-trained on the ImageNet dataset):

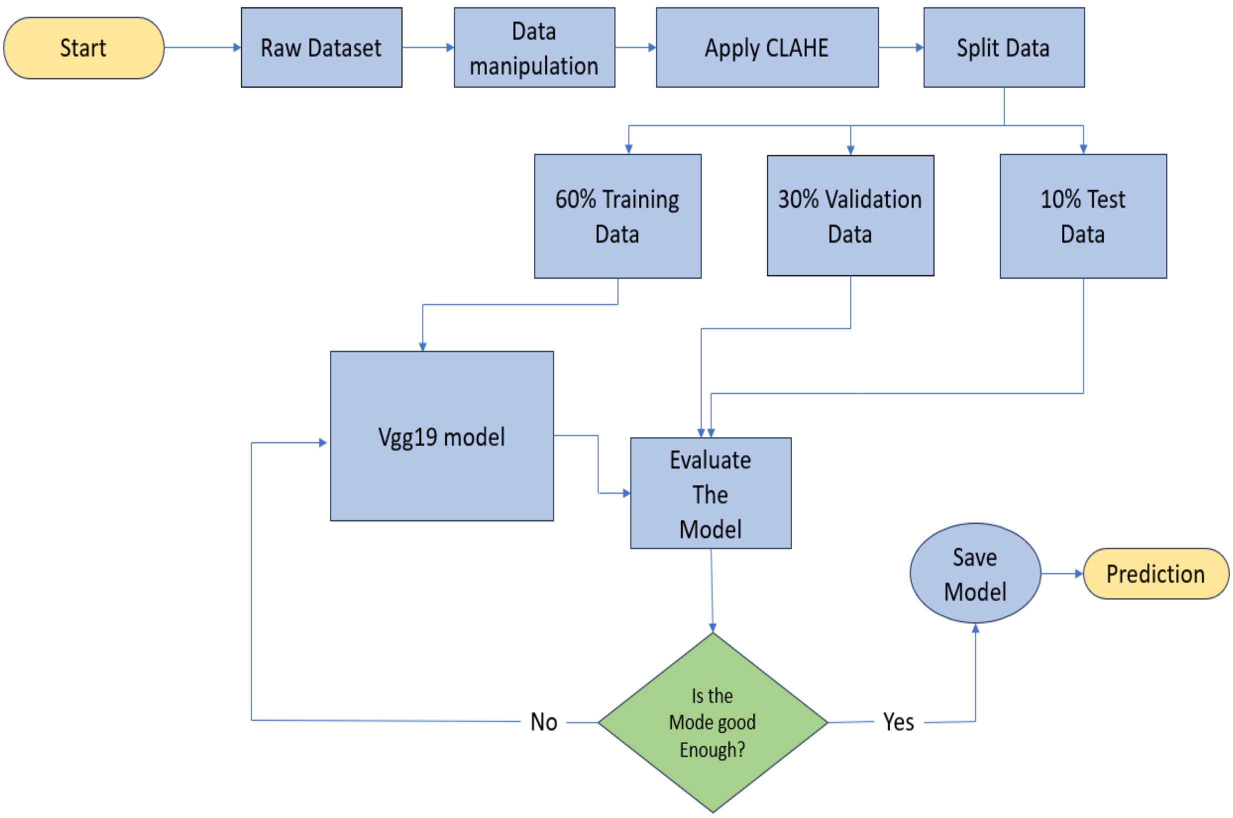
- VGG19 has 16 convolution layers, 3 Fully connected layers, with the final fully connected layer having SoftMax activation function as the non-linear part.
- The base convolutional layers having pre-trained weights were frozen.
- For our classification network: We used two dense layers. The final dense layer has four neurons (one for each class) and the activation function as SoftMax activation.
- For fine-tuning, we unfroze the base convolutional layers and ran the model for additional 10 epochs or the callbacks stopped the model from training.
- For classification, total trainable parameters were 100,356, while non-trainable were 20,024,384. Whereas for fine-tuning, they were 20,124,740 and 0 respectively.
- The network was trained with call-backs, to stop training the network in case of over-fitting.
- Training parameters:
    1. Loss Function: Categorical Cross entropy
    2. Optimizer: ADAM

The pre-trained weights helped a lot in adjusting the classification network to our dataset. VGG19 showed significant improvement in accuracy and loss values. This model clocked out at 75% accuracy and a loss of 0.6844 after fine tuning.

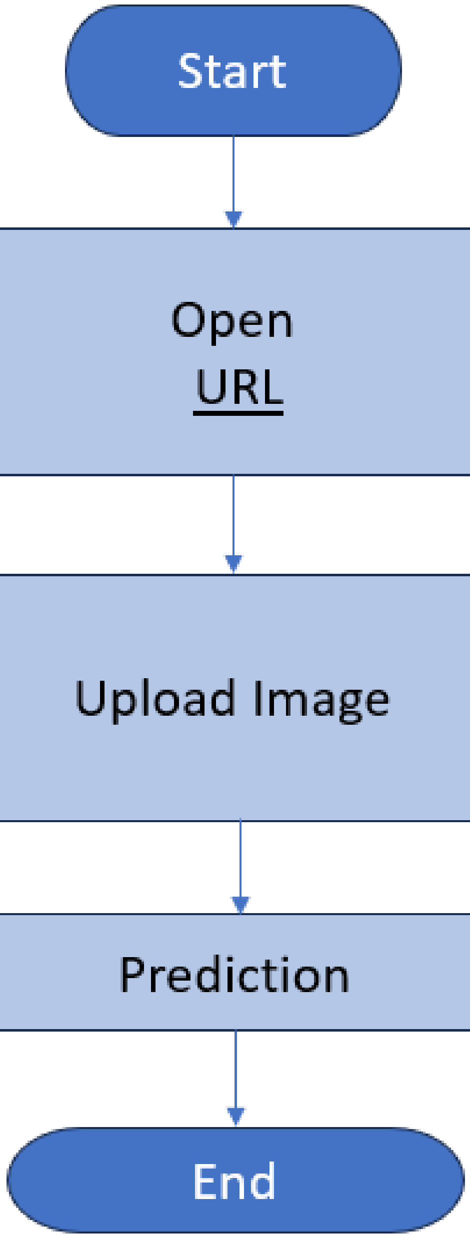
Chapter 4

SYSTEM DESIGN AND FLOWCHART

4.1 Flowchart for ML Model



4.2 Flowchart for Frontend



Chapter 5

FINDINGS AND CONCLUSIONS

5.1 Conclusion

Using transfer learning techniques on the VGG19 model in study, we compensate the requirement of more data samples to train a deep learning model.

5.2 Future Works

We intend to enhance our dataset classification by exploring 'multi-label, multi-class techniques. Our approach involves identifying datasets containing related eye diseases, preprocessing and merging them to create a larger dataset. Subsequently, we will train VGG19 from scratch. This expanded dataset will enable us to evaluate a broader range of pre-trained models, establishing a benchmark for our research.

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