EyeDetect (2)

by Pratham R Shetty

EyeDetect: Image based Classification on Eye Diseases

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***Abstract*—Keratitis, more commonly known as Corneal Ulcers are open sores on the cornea that can lead to serious vision loss if left untreated. This makes it highly necessary to diagnose them quickly and accurately. Traditional diagnostic methods, however, are highly limited in providing a diagnosis for these types of ulcers. This project aims to overcome such challenges by using deep learning models for the classification of corneal ulcers. In this project, we evaluate an AI model -based on Convolution Neural Networks (CNN) - on the SUSTech-SYSU dataset [1], a dataset of images of corneal ulcers. Our goal is to find an efficent and accuracte model that can detect and classify corneal ulcers that can be adopted in clinical settings, thereby revolutionizing the diagnostic process for corneal ulcers, changing the way corneal ulcers are diagnosed, and improving patient care. Index Terms—CNN, Deep Learning , MobileNetV2, Eyes, Disease, Corneal Ulcers**

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I. Introduction

Corneal ulcers, or keratitis are open sores present on the cornea of the eye. The symptoms or characteristics are red and watery eyes. They can cause severe eye pain and discharge of pus from the eye, and lead to vision loss and blindness if they are not treated properly. The traditional ways of diagnosing these ulcers rely heavily on doctor's expertise in interpreting symptoms, and so often have issues in consistent and early detection. The advent of machine learning and artificial intelligence offers a new solution with tools that could potentially overcome these limitations through automated, precise, and rapid disease identification and classification.

In the realm of Eye Diseases, AI has had a great potential as it allows for automatic processing and analysis of images. AI helps in identifying diseases like corneal ulcers much quicker and earlier, and thus increasing the accuracy, speed, and accessibility of disgnoses. This is especially important for diseases like corneal ulcers, as early detection of the ulcers and accurate classification and determination can dramatically alter the outcomes of the ulcer treatment and prevent progression of the disease to more severe stages. No longer do we need to wait for a specialized eye doctor to be present before we can book an appointment with the hospital. AI can now process, analyze and classify the images of the ulcers with great accuracy. The SUSTech-SYSU dataset [1], with its extensive categorization and grading of corneal ulcers, provides an opportunity to explore and make benchmarks of the effectiveness of various AI models in a domain where precision is highly necessary.

While there has been considerable research done on the individual capabilities of machine learning models in the context of diagnosing eye diseases, there are still many models that are as of today still unexplored. We aim to fill this gap by fine-tuning a unexplored model on the SUSTech-SYSU dataset [1] for automatically segmenting and classifying corneal ulcers.

This paper focuses on fine-tuning an existing model as of yet unexplored for this purpose, in a way that can maximize the accuracy of the model and to determine it's efficacy in the segmentation and categorization of corneal ulcers using the SUSTech-SYSU dataset [1]. We begin with a brief overview of corneal ulcers and the significance of AI in their diagnosis, setting the stage for our research. The subsequent sections detail the methodology employed in selecting, implementing, and evaluating the AI model. The discussion extends to the implications of our findings for clinical practice, highlighting how these AI models can support ophthalmologists in diagnosing corneal ulcers more effectively. We conclude with insights into future research directions and the potential for integrating AI into routine ophthalmological diagnostics.

II. Literature Survey

In recent research that explores integrating machine learning applications into ophthalmology, various models and techniques have been employed to enhance the detection and classification of eye diseases. Ramanathan et al. used traditional machine learning algorithms to facilitate the early detection of serious eye diseases such as cataracts and glaucoma, and used ROC curves to evaluate model performance [2]. Toki et al. introduced "RetinalNet-500," a Convolutional Neural Network designed specifically to analyze retinal fundus images for signs of eye diseases [3]. Saini et al. also furthered the use of CNNs in the medical field by utilizing EfficientNetB3 in their deep learning model to classify various eye conditions, showcasing the high precision of CNNs in distinguishing between normal and pathological findings [4]. Selvathi and Suganya applied a support vector machine (SVM) approach to detect diabetic eye disease using thermal imaging, a method that demonstartes the potential for SVM in handling alternative medical image formats [5]. These studies collectively highlight the general types of innovative application of machine learning technologies to significantly improve diagnostic processes within the field of ophthalmology.

For segmentation of corneal ulcers, several methodologies have been explored to enhance the accuracy and efficiency of the processes. Portela et al. (2021) implemented a combination of U-net and DexiNed, followed by post-processing techniques to achieve a Dice Coefficient of 70.50% and a specificity of 99.0% [6]. This approach emphasizes the utility of integrating multiple neural network architectures to capture both the general shape and precise edges of ulcers. Wang et al. (2021) introduced "Cu-segnet," a dedicated deep learning network designed to precisely delineate ulcer regions, which makes use of the inherent capabilities of neural networks to manage the complexity of medical image segmentation. Though specific performance metrics are not disclosed, the focus is on improving the precision of segmentation, something that is crucial for subsequent diagnostic and treatment processes [9].

Classification of corneal ulcers has also been done using deep learning and machine learning techniques. Sevli (2023) explored the effectiveness of various CNN models, where AlexNet and VGG16 achieved accuracies of 95.34% and 98.14% respectively, and a newly developed CNN model reached a perfect accuracy of 100% [5]. This study demonstrates the potential of tailored deep learning models to surpass traditional methods in clinical accuracy and efficiency. Lv et al. (2022) utilized a Multi-scale Information Fusion Network combined with label smoothing to classify corneal ulcers from slit lamp images, achieving an accuracy of 87.07% [8]. Their approach highlights the advantages of integrating features at various scales and applying label smoothing so as to improve model robustness against label noise, thereby increasing classification performance.

Lyu et al. (2020) applied transfer learning to automatically segment the cornea from ocular staining images, achieving a Dice score of 95.82% [6]. This methodology capitalizes on the strength of pre-trained networks to enhance segmentation tasks with limited datasets. Inneci and Badem (2023) combined genetic algorithms with a Residual Neural Network (ResNet) to select optimal image features for corneal ulcer classification, although specific accuracy improvements were not detailed. Their approach shows the integration of evolutionary algorithms with deep learning to refine feature selection and improve diagnostic performance, illustrating a novel methods to handle the complexity of medical image analysis [8].

These studies together depict a significant shift towards more and more accurate methodologies in the diagnosis and classification of corneal ulcers and even some other ocular diseases using advanced computational technologies. The integration of deep learning, genetic algorithms, and transfer learning not only enhances the accuracy but also the applicability of these models in hospitals and clinics, helping in making highly substantial improvements to patient care and treatment outcomes.

III. Proposed Methodology

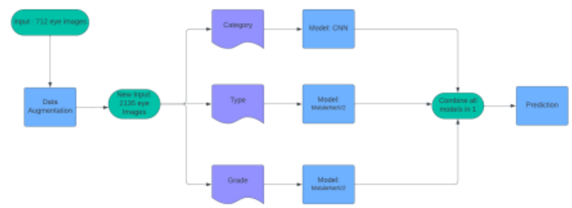

Fig. 1. High Level Design Diagram of Methodology

The project EyeDetect comprises of many steps as shown in Fig. 7:

1) Input : Based on available data [1] there are 712 images present as input and a label.csv which has a path of all the images and describes the category, type and grade of the eye disease the image represents.
2) Data Augmentation: All the images are augmented i.e. rotated, flipped, grayscaled etc; and appended back into input. This improves the correctness of prediction.
3) Feature extraction: The features are extracted from input which will be used by the model.
4) Model Building: Three models are used for each label namely category, type and grade. All the images passed through each of these three models are trained for each label separately and are classified.
5) Testing : Each of the models are tested using the test data and we get the performance metrics of the model.

IV. Implementation

A. Dataset Description

The dataset [1] as shown in Table-1 contains the path directory of 712 images of eyes and 3 attributes namely category, type and grade .

The classes in category, type and grade are described below:

1) Category:
   Category 0: point-like corneal ulcers
   Category 1: point-flaky mixed corneal ulcers
   Category 2: flaky corneal ulcers
2) Type:

TABLE I
SAMPLE OF LABEL.CSV

Name	Category	Type	Grade
1.jpg	0	4	3
2.jpg	0	4	3
3.jpg	0	2	2
4.jpg	0	2	1
5.jpg	0	1	3

type 0 : No ulcer of the corneal epithelium
type 1 : Micro punctate
type 2 : Macro punctate
type 3 : Coalescent macro punctate
Type 4: Patch ($\geq$ 1 mm)

3) Grade:
grade 0 : No ulcer of the corneal epithelium
grade 1 : Corneal ulcers involve only one surrounding quadrant
grade 2 : Corneal ulcers involve two surrounding quadrants
grade 3 : Corneal ulcers involve three or four surrounding quadrants
grade 4 : Corneal ulcers involve the central optical zone of the cornea

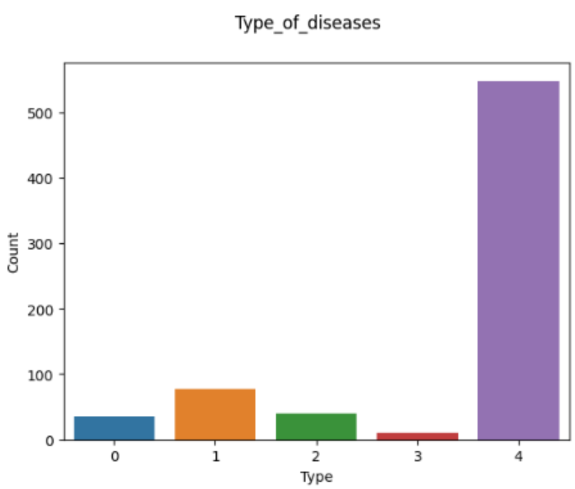

Fig. 2. Type Distribution in initial Dataset

B. *Experimental Setup*

This section describes the experimental setup used by EyeDetect to classify images for predicting category, type and grade of the eye disease.

1) Hardware Configuration: The experiment was carried out in a computing system hosted on Kaggle platform, utilizing the following GPU instance:

GPU: NVIDIA Tesla T4
29GB RAM

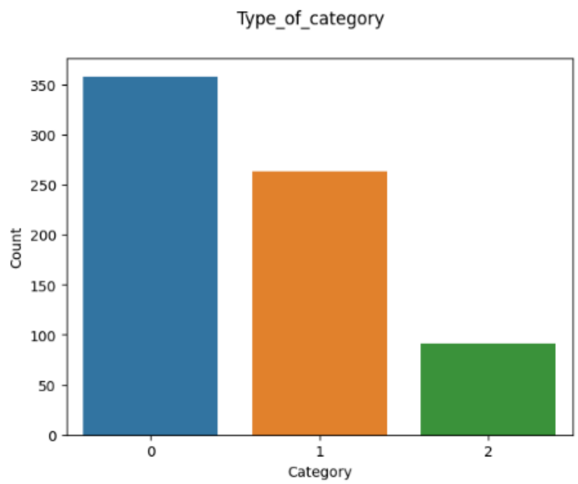

Fig. 3. Category distribution of initial Dataset

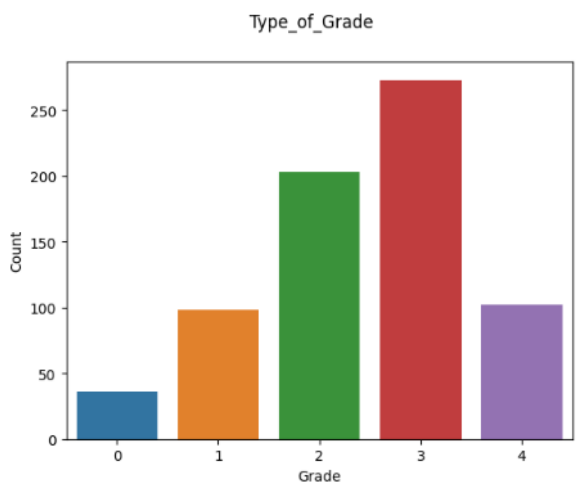

Fig. 4. Grade Distribution of initial dataset

2) Software Libraries: The following software libraries were used during the experiment:

Pandas, Numpy, Os, Matplotlib, Seaborn, Shutil, OpenCV, Keras, TensorFlow, tqdm

C. *Implementation Models*

The models that haven been chosen for EyeDetect have shown good values of the evaluation metrics.

The models are - a user defined CNN (for category) and MobileNetV2 (for grade and type).

1) Convultional Neural Network (CNN): A Convolutional Neural Network (CNN) is a type of deep learning architecture designed specifically for processing structured grid-like data, such as images. It consists of multiple layers, which each layer performing a specific operation so as to extract hierarchical representations from the input data. The key components of a CNN include convolutional layers, pooling layers, and fully connected layers.

1. Convolutional Layer : The convolutional layer applies a set of learnable filters (kernels) to the input image to extract local features through a convolution operation.

2. Pooling Layer : The pooling layer downsamples the feature maps obtained from the convolutional layers to reduce spatial dimensions and control overfitting. Common pooling operations include max pooling and average pooling, where each output value is computed by applying a pooling function (e.g., max or average) over a local region of the input feature map.

$$n_{\text{out}} = \left\lfloor \frac{n_{\text{in}} + 2p - k}{s} \right\rfloor + 1 \tag{1}$$

where
n_{in} : number of input features
n_{out} : number of output features
k : convolution kernel size
p : convolution padding size
s : convolution stride size

CNNs leverage the hierarchical pattern learning enabled by these layers, with succeeding layers learning more complex and abstract features based on the activation function values of previous layers. The final layers typically involve fully connected layers followed by softmax (for classification tasks) or sigmoid (for binary classification) activation functions so as to produce the network's output predictions. Utilizing training alongside backpropagation of weights and optimization algorithms such as gradient descent, CNNs can learn to automatically extract relevant features and make accurate predictions on image data.

2) MobileNetV2: MobileNetV2 is a specially designed convolutional neural network (CNN) architecture. It is specifically desgined for efficient and lightweight deep learning to be performed on mainly mobile devices but also other types of edge devices. It was introduced to be an improvement over the original MobileNet model, and was aiming to achieve a higher accuracy all the while requiring a low cost for computational resources and a low memory footprint. The key innovation of MobileNetV2 lies in its use of inverted residual blocks with linear bottlenecks. This design enables the network to capture and detect complex patterns and features efficiently by using lightweight depthwise separable convolutions.

Each inverted residual block in MobileNetV2 consists of a sequence of operations.A lightweight depthwise convolution is followed by a linear bottleneck layer. This layer expands and then projects the feature maps back to a lower-dimensional space. This design of layers helps in reducing the number of parameters and computations needed for the model as compared to the more traditional convolutional layers. This makes MobileNetV2 very well-suited for resource-constrained environments like mobile devices.The "Linear Bottleneck" layer of MobileNetV2 is a new style of layer that facilitates the use of the model in learning rich representations over a minimal computational cost.

Overall, MobileNetV2 provides an effective solution for the deployment of deep neural networks on mobile devices with limited or constrained computational resources, all the while maintaining a competitive performance compared with other CNN models in various tasks such as image classification and object detection.

D. Implementation Steps

The steps involved in implementation process are :

1) Augment the images in dataset [1] to 2135 images to improve overall accuracy and to avoid overfitting.
2) Split the images into training and testing image sets and use them to train the models.
3) Training and evaluating 3 models:
   Category: CNN
   Type: MobileNetV2
   Grade: MobileNetV2
4) The output of 3 models is combined to give final output which tells which category, type, grade of eye disease the patient got. Use the combined model for prediction.

V. Results

The results are validated using performance metrics i.e. accuracy score and confusion matrix.

Table-2 shows accuracy scores for the 3 labels category , type and grade.

TABLE II
ACCURACY OF MODELS

Value to Predict	Model	Training Accuracy	Test Accuracy
Category	CNN	0.755	0.715
Type	MobileNetV2	0.904	0.842
Grade	MobileNetV2	0.928	0.661

Tables 3,4 and 5 show the confusion matrix for the 3 labels category, type and grade.

TABLE III
CONFUSION MATRIX - CATEGORY

	precision	recall	f1-score	support
0	0.72	0.91	0.81	310
1	0.70	0.68	0.69	257
2	0.80	0.05	0.10	74
accuracy			0.72	641
macro avg	0.74	0.55	0.53	641
weighted avg	0.73	0.72	0.68	641

Figures 5,6 and 7 display the training progress of the 3 models.

VI. Conclusion

The major limitation in this project is that dataset we have chosen [1] is very small (about 248MB) , and even after augmentation of the data by rotation, flipping and scaling it is still small (668MB) which means that the models utilized may be overfitting in some cases. Another major limiation of

TABLE IV
CONFUSION MATRIX - TYPE

	precision	recall	f1-score	support
0	0.50	0.30	0.38	33
1	0.67	0.52	0.59	61
2	1.00	0.19	0.33	36
3	0.00	0.00	0.00	9
4	0.87	0.98	0.92	502
accuracy			0.85	641
macro avg	0.61	0.40	0.44	641
weighted avg	0.83	0.85	0.82	641

TABLE V
CONFUSION MATRIX - GRADE

	precision	recall	f1-score	support
0	0.60	0.36	0.45	33
1	0.59	0.53	0.56	89
2	0.62	0.64	0.63	184
3	0.72	0.77	0.74	245
4	0.62	0.62	0.62	90
accuracy			0.66	641
macro avg	0.63	0.58	0.60	641
weighted avg	0.65	0.66	0.65	641

the dataset is that it is highly biased towards type 4 corneal ulcers. This is due to a higher percentage of the images being of type 4 ulcers as they are more commonplace in real-life. But this causes issues in model training due to lower amout of samples for the other types of ulcers.

The main objective of the project "Eye Detect" is to improve the precision and accuracy for the classification of corneal ulcers so as to reduce the time taken in diagnosis and to give good insights to the medical professionals in a way that will help in taking good decisions. The outcome of this research is the improvement in accuracy as compared to previous researches but there is still scope of improvement that can be worked upon.

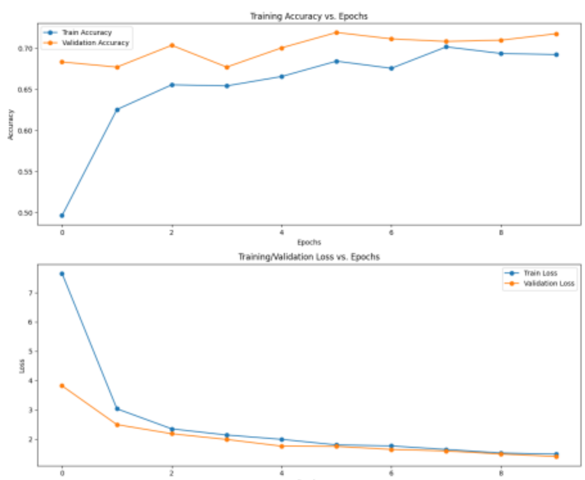

Fig. 5. Category Model Training

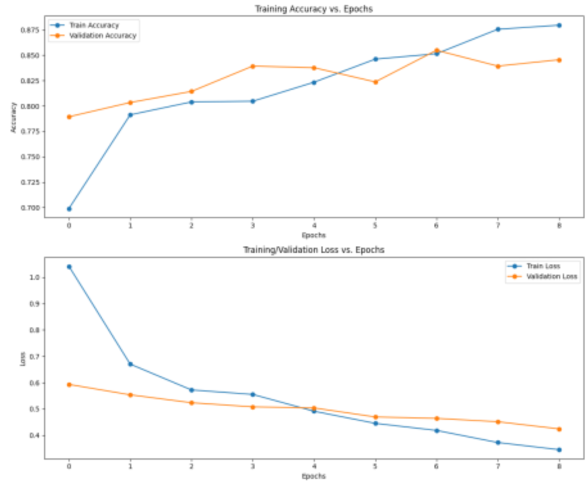

Fig. 6. Type Model Training

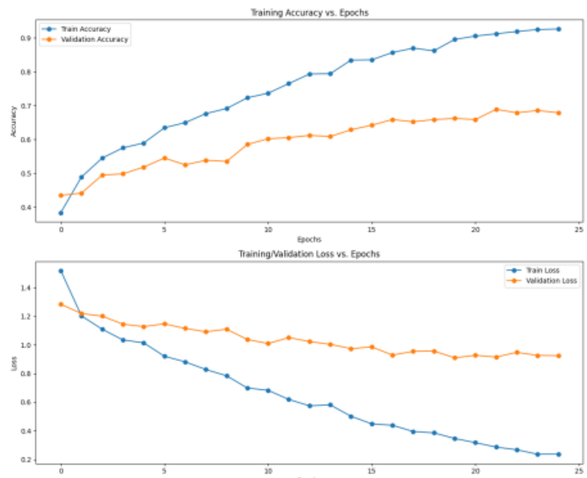

Fig. 7. Grade Model Training

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