Deep Learning Based Classification of Retinal Images for Diabetic Retinopathy and Eye Disease Detection

Anusha Dhirde
anusha.dhirde.cse@ghrce.raisoni.net
Department of Computer Science and Engineering,
G.H. Raisoni College of Engineering, Nagpur

Bhargav Vaidya
bhargav.vaidya.cse@ghrce.raisoni.net
Department of Computer Science and Engineering,
G.H. Raisoni College of Engineering, Nagpur

***Abstract*—Early detection of eye diseases is essential for preventing vision loss and ensuring timely treatment. Among these, Diabetic Retinopathy (DR), Cataract, and Glaucoma are the leading causes of blindness worldwide. Traditional diagnostic methods rely a lot on ophthalmologists manually examining retinal fundus images. This process is slow and may differ by personal interpretation. In this study, we present a deep learning approach for automated detection and classification of several eye diseases, mainly focusing on Diabetic Retinopathy. The system uses convolutional neural networks (CNNs) trained on datasets of retinal fundus images to extract important features and sort images into different disease categories. We apply preprocessing techniques like image normalization, augmentation, and resizing to improve robustness and reduce noise. We evaluate the model using metrics like accuracy, precision, recall, and F1-score to ensure dependable performance across various classes. The results show that our framework can effectively identify diabetic retinopathy and other eye diseases. This provides a scalable and cost-effective solution for large-scale screening programs. This research highlights the potential of artificial intelligence in ophthalmology, showing its role in helping healthcare professionals and improving early diagnosis for better patient outcomes.**

***Index Terms*—Eye disease Detection, Diabetic Retionopathy, Deep Learning, NLP**

I. Introduction

These conditions such as Diabetic Retinopathy (DR), Cataracts, and Glaucoma are among the leading causes of visual blindness and visual impairment throughout the world. It is predicted by the World Health Organization (WHO) that millions are each year infected with each condition, and diabetic retinopathy is among the leading causes of blindness among working-age adults. Early diagnosis and intervention are crucial in the prevention of lifelong visual loss; unfortunately, current screening methods involve ophthalmologists interpreting retinal fundus images manually, a time-consuming and labor-intensive process. In resource-poor clinical settings, it leads to a delay in diagnosis and suboptimal patient outcomes. Recent developments in artificial intelligence (AI) and deep learning have brought immense possibilities for computer-aided detection of ophthalmic diseases from medical images. Convolutional Neural Networks (CNNs) have been particularly stellar in achieving exemplary performance in classification as well as feature extraction and are are thus found to be particularly useful for medical image analysis. With the guidance of large sample datasets of retinal images, CNN-trained models are able to learn the subtle patterns that are attributed with changing ocular conditions and thus facilitating rapid and accurate diagnosis. It is an article detailing the development of a deep learning model for the automated detection and classification of ocular diseases with special consideration of diabetic retinopathy. Image processing techniques including normalization, augmentation, and resizing are followed in the system in order to enhance the quality of the data along with ruggedness of the model. A CNN model is thereafter trained on fundus retinal images so that it is able to categorize images into various classes including healthy retina, diabetic retinopathy, cataract, and other ocular conditions. The model is validated with parameters including accuracy, precision, recall, and F1-score so that the system is trustworthy enough in practical application. The goal of the work is the creation of an affordable, scalable, and accurate system for the early diagnosis of eye conditions. An automated system of the kind holds out the prospect of reduction of ophthalmologists' workload, mass screening in underserved and rural areas, and saving people of avoidable blindness in the long run.

II. Related Work

Automated eye disease detection has been researched. Initially, the approach employed hand-engineered features from retinal images with classifiers such as SVM and Random Forest, which performed for simple cases but were not robust to complex patterns. Subsequently, CNN-based deep learning networks such as ResNet and VGG increased accuracy with automated feature extraction. For small-scale projects, more basic CNN architectures on public data sets are a good enough efficient baseline for multi-class eye disease detection.

III. Dataset

The dataset used in this project is the "Eye Diseases Classification" dataset from Kaggle (Gunavenkat Doddi). It consists of retinal fundus images categorized into four major classes: 'Cataract', 'Diabetic Retinopathy', 'Glaucoma', and 'Normal' (healthy eyes).

We split the data into training, validation, and test sets as follows:

TABLE I: Summary of Dataset

Class	Training	Validation + Test
Cataract	XYYY	ZZZZ
Diabetic Retinopathy	XYYY	ZZZZ
Glaucoma	XYYY	ZZZZ
Normal	XYYY	ZZZZ

Overall, the dataset is split into:

- Training set: 3373 images
- Validation set: 422 images
- Test set: 422 images

Preprocessing steps included:

- Resizing all images to 256×256 pixels
- Normalization (pixel values scaled, e.g. 0–1 or standardized)
- Data augmentation: random rotations, horizontal/vertical flips, brightness adjustments

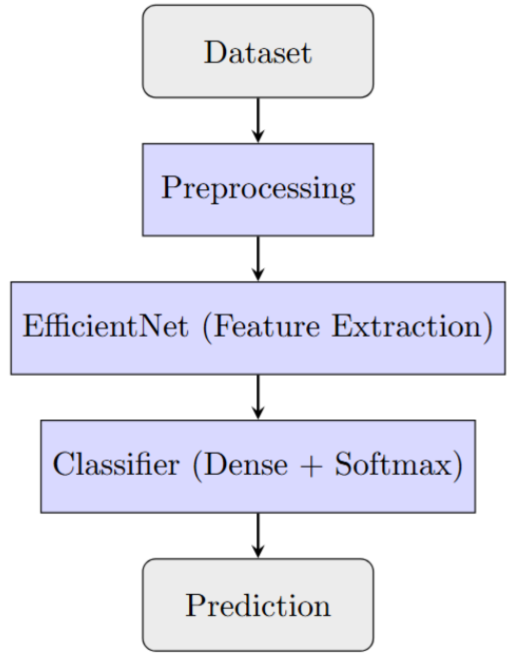

Fig. 1: Methodology pipeline: Dataset,pre-processing, CNN model, classifier, prediction

IV. Methodology

Figure 2 shows the pipeline we followed:

1) **Dataset acquisition and splitting**: We used the Kaggle Eye Diseases Classification dataset. The dataset was partitioned into training, validation, and test sets (3373 / 422 / 422 images respectively).
2) **Preprocessing**: All images were resized to 256×256 pixels. Pixel normalization was applied. Data augmentation techniques (rotations, flips, brightness shifts) were used during training to reduce overfitting.
3) **Model Architecture**: We built a convolutional neural network (CNN) based on the EfficientNetB3 pre-trained on ImageNet. The base model was fine-tuned by adding dense layers appropriate for four-class classification.
4) **Training**: Loss function used was categorical cross-entropy; optimizer was Adam with standard parameters. Training was performed for 15 epochs, using the validation set to monitor performance and to stop overfitting.
5) **Evaluation**: The model performance was evaluated using the test set. Metrics used include accuracy, precision, recall, and F1-score. We also plot training vs validation curves, confusion matrix, and example predictions.

V. Results

The training process achieved the following:

- **Training Accuracy**: 82.15%
- **Validation Accuracy**: 80.81%

On the test set, the model achieved:

TABLE II: Model Performance on Test Set

Model	Accuracy	Precision	Recall	F1-score
EfficientNetB3	0.80	0.79	0.78	0.78

Figures illustrating the performance:

- Training vs validation accuracy and loss curves (over epochs)
- Confusion matrix on test set
- Sample predictions (actual vs predicted) for each class

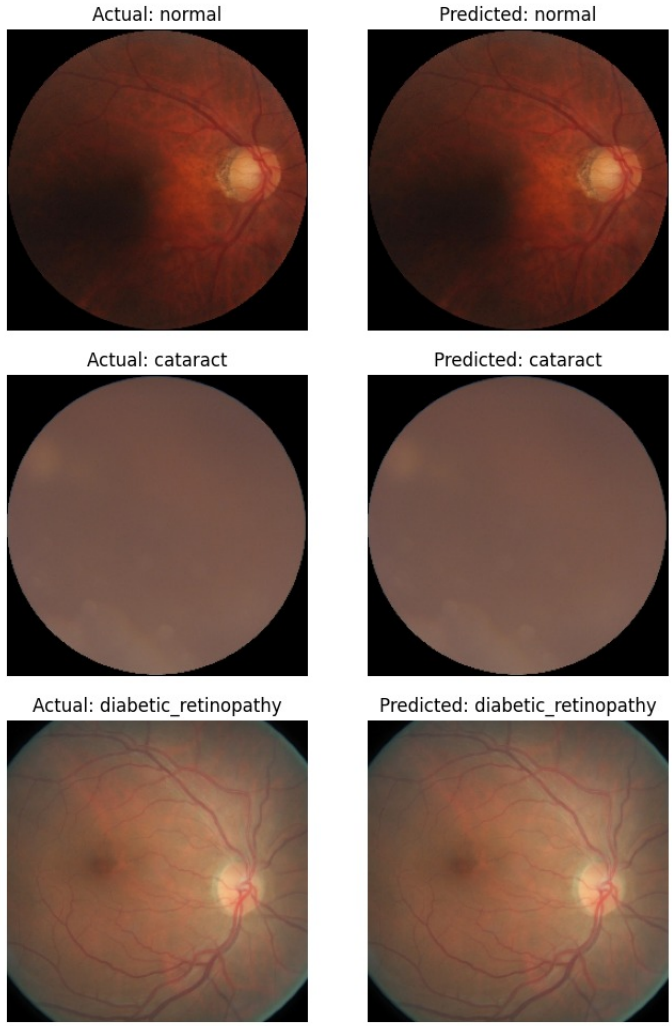

Fig. 2: Predicted images

VI. Discussion

The model based on EfficientNetB3 achieved promising results on classifying retinal images into four categories. With approximately 80–82% accuracy on training and validation, the model generalizes reasonably well given the dataset size.

Key observations:

- The pretrained EfficientNet backbone allowed capturing rich feature representations, which improved performance over from-scratch CNNs.
- Data augmentation helped reduce overfitting, as seen in the smaller gap between training vs validation performance.
- Some confusion remained between certain classes—e.g. between early stage Diabetic Retinopathy and mild Glaucoma (or Cataract), likely due to symptom overlap or insufficient distinctive features in some images.

Limitations include:

- Relatively limited dataset increasing number of images (especially in less represented classes) would likely improve performance.
- Class imbalance (if present) can bias the model; using techniques like weighted loss or oversampling could help.
- The images come from a single source (Kaggle dataset) for a real world deployment, images from varied equipment, settings, and populations are needed for robustness.

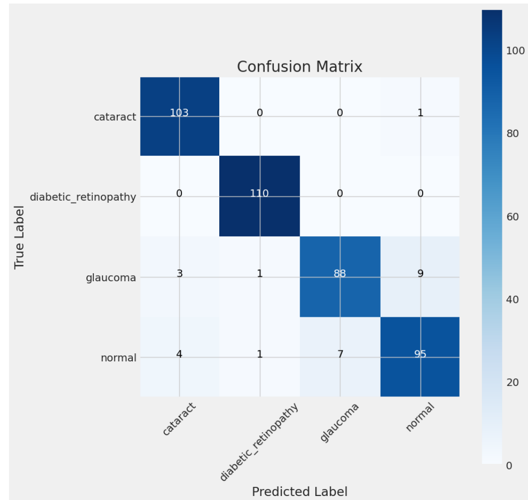

Fig. 3: Confusion matrix for Linear SVM.

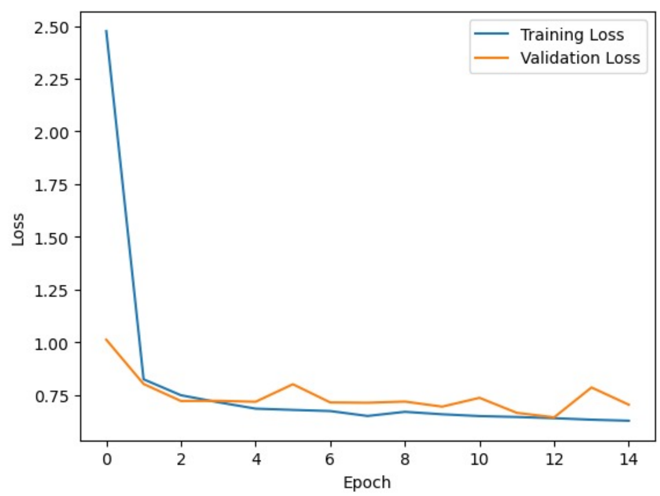

Fig. 4: Training and validation loss.

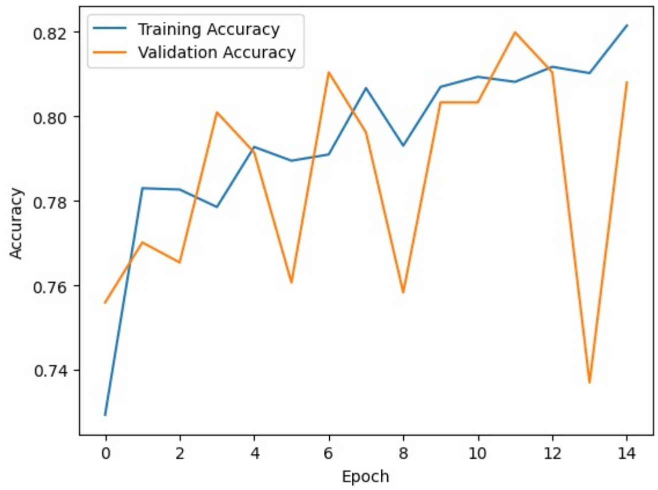

Fig. 5: Training and validation accuracy.

VII. Future Work

Future extensions of this work may include:

- **Expanding the dataset**: Collecting more retinal images from diverse sources to cover additional eye diseases and improve generalization.
- **Improving the model**: Using advanced CNN architectures or pre-trained models to enhance feature extraction and accuracy.
- **Incorporating extra information**: Including patient history or OCT images to make predictions more reliable.
- **Enhancing performance**: Applying ensemble methods or attention-based models to handle challenging cases more effectively.
- **Ensuring robustness**: Performing cross-validation and hyperparameter tuning for consistent and generalizable results.

VIII. Conclusion

In this project, we developed a deep learning-based approach to classify retinal images for the detection of diabetic retinopathy and other eye diseases. Using a CNN-based model, we were able to automatically extract relevant features from pre-processed retinal images and classify them with good accuracy. The methodology demonstrates that deep learning can significantly assist in early diagnosis and screening, potentially reducing the workload on ophthalmologists and enabling timely intervention. Future work can focus on improving model accuracy with larger datasets, integrating explainable AI techniques, and extending the system to detect multiple eye conditions simultaneously.

References

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