Cataract Disease Detection Using Pre-trained Models

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***Abstract*—Early detection and prevention of Cataract disease can effectively contribute in reducing the impact of cataracts. In this study, we explore the effectiveness of deep learning algorithms implemented with three pre-trained models —MobileNet VGG19, and ResNet50— for cataract disease detection. These algorithms leverage image processing techniques and have shown promise in various computer vision tasks. Our objective is to predict which algorithm performs best in cataract detection. We use a dataset of retinal fundus images to train and evaluate the models. The results demonstrate the potential of deep learning in early cataract diagnosis, which can significantly improve patient outcomes. Our model was able to achieve an accuracy of 96.33%.**

Index Terms—Cataract Detection, Deep Learning, ResNet50

I. INTRODUCTION

Cataract [1], a common eye disease worldwide, poses an important public health challenge due to its impact on vision impairment and disorder [2] & [3]. Effective timely detection and intervention are crucial in order to mitigate the potential consequences of this condition. In this study, we introduce the effects of three pre-trained deep learning models— MobileNet [4], VGG19 [5], and ResNet50 [6]- for the detection of cataract disease from retinal fundus images. These models influences the use of convolutional neural networks (CNNs) and transfer learning techniques, allowing them to learn and extract the most valuable features from large-scale datasets. By fine tuning these algorithms, our aim is to identify the most accurate and efficient approach for early cataract detection. Our research contributes to the increasing scale of knowledge in ophthalmology and computer vision, highlighting the role of deep learning methods in enhancing patient care. By automating the process of detection, we can develop clinical workflows, reduce diagnostic delays, and improve the quality of life for individuals affected by cataracts.

II. RELATED WORK

A. Exploiting ensemble learning for automatic cataract detection and grading by JJ Yang et al. Yang used machine learning techniques such as ensemble learning for the task of cataract disease detection. The best performance achieved was 93.2% and 84.5% in terms of the correct classification rates for cataract detection and grading tasks, respectively. [7]

B. Automated Detection of Cataract Using a Deep Learning Technique by R. Angelina et al. Angelina utilized the VGG16 pre-trained convolutional neural network model on retinal fundus images dataset and was able to achieve 92.1% in terms of accuracy in cataract disease detection. As a positive point for this approach, the researchers were able to utilize smart phone images along with the primary dataset. A challenging point is the complicated approach for generalizing to different populations. [8]

C. Automated Cataract Detection and Grading Using Deep Convolutional Neural Networks by Zhang et al. Zhang implemented his work using DCNN Architecture which benefit from hierarchical feature learning through convolutional layers. The output was classifying cataracts into severity levels (e.g., mild, moderate, severe). The researchers were able to achieve accuracy of 90.88% on the collected images. [9]

III. DATASET

In our project, we used Ocular Disease Recognition ODIR-5K dataset [10], which encompasses numerous of labeled eye images. Images are categorized by eye diseases, such as cataracts, glaucoma, and normal. The dataset also includes patient metadata, which is not relevant to this investigation. This study used 1088 images from the dataset, creating a balanced subset suitable for the task of binary classification as shown in Fig. 1

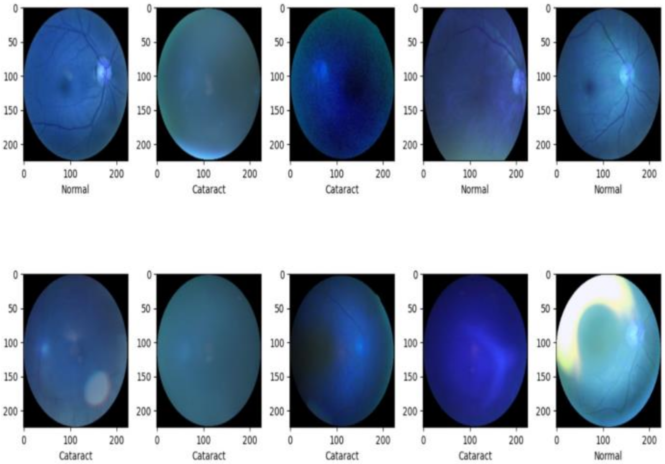

Fig. 1. Dataset Samples

IV. Methodology

A. Data Preprocessing

The data preprocessing included the following operations:

- Resizing: All images were resized to a squared dimensions of 224x224 pixels to match the input size requirement of the VGG19 architecture.
- Normalization: Pixel values were normalized to the range [0, 1] to help the model converge during training.
- Augmentation: To increase the robustness of the model against over-fitting and to simulate a variety of data acquisition conditions, data augmentation techniques such as horizontal flipping and rotation. We also added a gaussian noise [11] to enhance the robustness of our models against variations in input data. This additionally helped in improving the generalization capability, making the models more reliable in practical applications. Gaussian noise can be expresses as described in equation 1:

$$y(t) = x(t) + n(t) \tag{1}$$

where:

- $y(t)$ is the observed signal
- $x(t)$ is the original signal
- $n(t)$ is the Gaussian noise, typically modeled as $n(t) \sim N(0, \sigma^2)$, meaning it is normally distributed with a mean of 0 and variance σ^2

The probability density function of Gaussian noise $n(t)$ is given by:

$$p(n) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{n^2}{2\sigma^2}\right) \tag{2}$$

B. Model Archticture

Our model was based on ResNet50 architecture, as described in Fig. 2, as it was able to achieve the highest accuracy among other pre-trained models. ResNet is a powerful convolutional neural network (CNN) that has demonstrated remarkable performance in various image classification tasks. Developed by He et al. in 2015, ResNet50 introduced the concept of residual learning, which helps in training very deep networks by mitigating the vanishing gradient problem. This makes it an excellent choice for complex tasks like cataract detection in medical imaging.

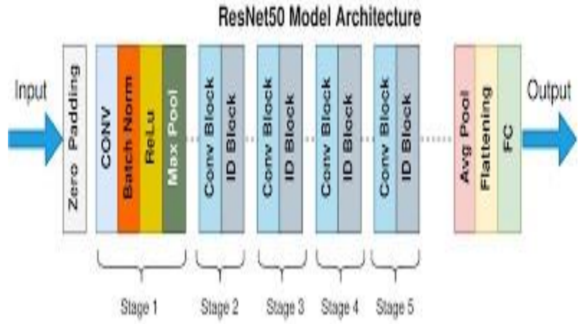

Fig. 2. ResNet50 Architecture

The three pre-trained models were used with the following hyperparameters values, knowing that we chose Adam optimizer [12] as it dynamically adjusts learning rates for each parameter, which can lead to faster convergence and better generalization. And, its incorporation of both first and second-order moments of gradients makes it well-suited for non-stationary objectives and problems with large amounts of data:

TABLE I. Chosen Hyperparameters

Hyperparameter	Value
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Loss Function	Binary Cross-Entropy
Epochs	15
Callbacks	- Model Checkpoint: Saves the model with the best validation accuracy.
	- Early Stopping: Prevents overfitting by halting training when validation accuracy plateaus.

V. Results

A. Evaluation Metrics

Reaching an accuracy [13] of 96.33%, ResNet50 was able to achieve the highest accuracy between the three pre-trained models [14] & [15].

TABLE II. EVALUATION OF THE BEST MODEL

Class	Precision	Recall	F1-Score
0	0.98	0.94	0.96
1	0.95	0.98	0.97

B. Models Performance

In contemporary machine learning, especially in the areas of natural language processing and computer vision, the usage of pre-trained models is widespread. The method accelerates the learning process and improves accuracy as well, given that it provides a strong base that contains generic knowledge already.

1) MobileNet:

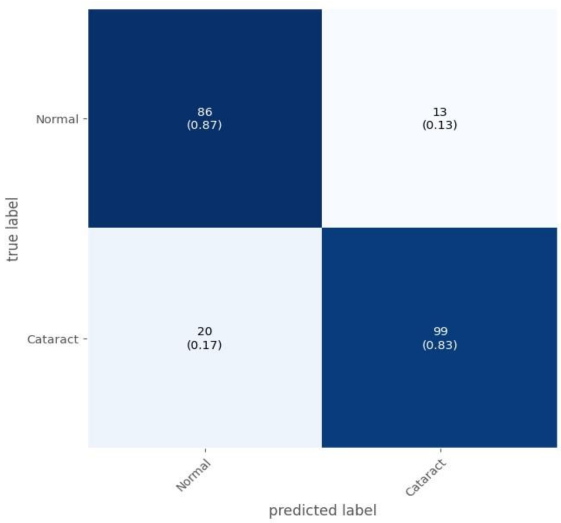

Fig. 3. MobileNet Confusion Matrix

MobileNets are more suitable for real-time mobile applications due to the face that it is a lightweight network. As a trade-off, MobileNet is relatively shallow architecture with reduced number of parameters, resulting in achieving the lowest accuracy between the three models, which is illustrated in Fig. 3.

2) VGG19:

Although its metrics were not the highest between the three models as shown in Fig. 4, It was able to achieve notable results considering the results mentioned in related works section.

3) ResNet50:

ResNet50 was able to achieve significant confusion matrix results with 0.98% of true negative values and only 6% of false positive values, and its accuracy and loss curves are illustrated in Fig. 5 & 6

C. Visual Assessment of Model Predictions

The ResNet50 model accurately diagnoses cataracts based on test photos, as demonstrated in Fig. 7. The model's efficacy is validated visually by annotating each image with both the predicted and actual label.

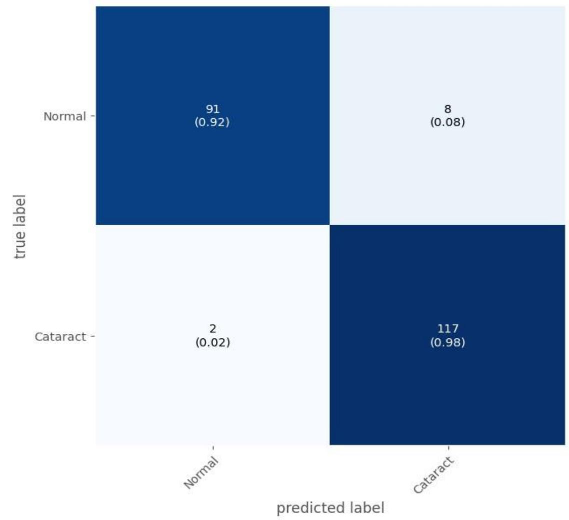

Fig. 4. VGG19 Confusion Matrix

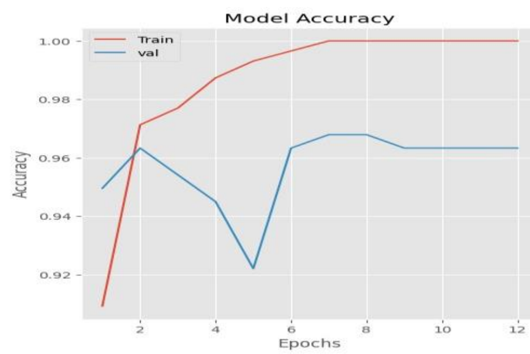

Fig. 5. ResNet50 Accuracy Curve

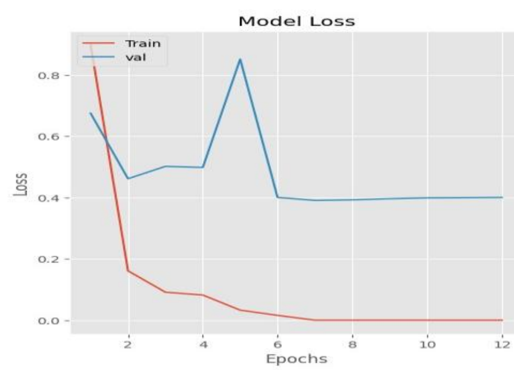

Fig. 6. ResNet50 Loss Curve

VI. CONCLUSION

In this study, we investigated the effectiveness of three pre-trained deep learning models—VGG-19, ResNet-50, and MobileNet—for the detection of cataract disease using retinal fundus images. Our objective was to identify the model that provides the highest accuracy for early cataract diagnosis. Through extensive training and evaluation using the ODIR-5K dataset, we found that the ResNet50 model achieved the best performance with an accuracy of 96.33%, significantly outperforming VGG-19 and MobileNet. The addition of a Gaussian noise layer before the ResNet50 model layer enhanced the robustness and generalization capability of the model, making it a reliable tool for practical applications. These results underscore the potential of deep learning in improving early cataract detection, which is crucial for timely intervention and better patient outcomes.

Despite the promising results, there are several avenues for future research to further enhance the effectiveness and applicability of deep learning models in cataract detection:

A. ***Incorporating Multi-Modal Data:***

Integrating additional data sources, such as patient demographics and clinical history, may provide a more comprehensive analysis and improve the predictive power of the models.

B. ***Real-World Validation:***

Conducting extensive validation of the models in real-world clinical settings to assess their performance in diverse and unstructured environments. This would involve collaborations with ophthalmologists and healthcare institutions.

C. ***Deployment and Scalability:***

Developing lightweight versions of the models suitable for deployment on mobile and edge devices to facilitate widespread use, particularly in resource-limited settings. By addressing these areas, we can continue to improve the utility of deep learning models in ophthalmology, ultimately leading to better diagnostic tools and improved patient care

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