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Eye Disease Detection And Classification Using Deep Learning: A Comperative Study

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Abstract*—Eye disease detection is a critical task in medical diagnostics, particularly for conditions that can lead to vision impairment or blindness if left untreated. Recent advancements in deep learning have demonstrated promise in enhancing accuracy and efficiency of medical image analysis. This research focuses on the development and evaluation of deep learning-based model for detecting various eye diseases using retinal images. The proposed model leverages convolutional neural networks (CNNs) to automatically extract property from retinal images and classify them into categories such as diabetic retinopathy, glaucoma, age-related macular degeneration, and cataracts. The experimental results demonstrate that the proposed deep learning model gains high accuracy, sensitivity and specificity in finding out eye disease from retinal images. We achieved an impressive 100% training accuracy, along with strong 94% validation and testing accuracy. We suffered relatively little loss. Additionally, we attained 100% recall, f1-score, and precision, demonstrating high performance. Comparative analysis with traditional image processing methods highlights the superiority of deep learning approaches in terms of both performance and computational efficiency.

***Keywords*—Eye Disease, CNN, Deep learning, Transfer learning.**

I. INTRODUCTION

The human body uses its eyes more than any other sense out of the five. The quality of life is greatly diminished for those who have vision issues. Glaucoma, cataract and diabetic retinopathy are the major three conditions affecting the eyes [1]. Glaucoma is a class of eye conditions which can cause eyesight damage and blindness by injuring nerve in the behind of individual's eye called the optic nerve Click or tap here to enter text.. A cataract is an opacification of the eye's lens. When a cataract progresses, a person may experience hazy vision, double vision, halos surrounding lights, and impaired night vision. Colors could appear faded [2]. Diabetic retinopathy is the most prevalent eye condition that develops in people with long-term diabetes (DR) [3]. In 2013, there were 64.3 million glaucoma sufferers worldwide[4]. Early identification of eye disorders can help provide appropriate care or, in the absolute least, prevent the worsening of these conditions. The physician-to-ophthalmologist ratio is 1:10,000, which is significantly below than the WHO's advised. Although it's limited because to low knowledge, a scarcity of ophthalmologists, and expensive consultation fees. Thus, automatic screening is critical [5].

Numerous research investigations have attempted to predict and classify an eye with a disease from one that is healthy using images of the eyes [6]. Proposed a CNN-based models LeNet and AlexNet, as well as the inception and ResNet models for detection of glaucoma and diabetic retinopathy and The best models were AlexNet and LeNet, with respective accuracy values of 97.96% and 97.40% [7] . Support Vector Machine classifier for detection of diabetic retinopathy and their result are compared. A 5-fold cross validation scheme is employed to maximize the adaptation strength of the proposed approach. Ms.Shreya proposed Convolutional Neural Network (CNN) model and grayscale fundus photos for the diagnosis of DR [8]. This research indicates that neural networks have significant therapeutic potential. Rahul proposed a CNN based eye disease detection model using 4130 dataset and obtain the accuracy of 94% [9]. Proposed a new custom convolutional neural network (CNN) alongside prominent architectures like SqueezeNet, VGG16, and ResNet50 and all these models are then combined with Long Short-Term Memory (LSTM) to improve detection of common eye disease [10].

Most of the researcher used only CNN based architecture for early detection of eye disease and obtain the accuracy lower than 95%. This aforementioned research gap motivated the author to write this paper and the main target of this paper is to explore the use of CNN and transfer learning for identification of eye diseases using retinal pictures. We investigate EfficientNet-B3 and Xception, two pre-trained models through the process of fine-tuning these models on a top-notch, publicly accessible retinal dataset obtained from Kaggle, our objective is to assess and contrast how well they perform in the classification of eye illnesses. By advancing the creation of automated diagnostic tools, this project hopes

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to improve eye disease management and treatment in the long run.

II. Related Work

Numerous scholars are committed to investigating the use of artificial intelligence in the detection of eye diseases. Using color fundus pictures to develop and evaluate deep learning (DL) models for automated diagnosis of eye-related disorders. It underscores the significance of using a variety of high-quality datasets to train reliable deep learning models and stresses the application of advanced image processing techniques to extract disease-relevant features [11].

The automatic detection of Diabetic Retinopathy using Deep Neural Network was proposed by Tariq, Hassan, et al. [12]. They employed the CNN-based Inception ResNet V2, GoogleNet, AlexNet, ResNeXt-50, and Inception V4 architectures. This method achieves an accuracy of around 84.01 percent for picture detection with the usage of supervised learning architecture.

The approach for classifying eye illness using hybrid convolution neural network-recurrent neural network models was created by Londhe, Mayuresh [13]. Long Short-Term Memory was employed for classification in this work, and Transfer Learning (InceptionV3, InceptionResNetV2, and DenseNet169) for characteristic extraction. The Kaggle dataset, that includes an inconsistent number of photos in each group and produced the best accuracy of 69.50%, is used in the study.

For the purpose of accurately diagnosing diabetic retinopathy, a deep convolutional neural network (CNN) comprising 18 convolutional layers and 3 completely linked layers was constructed in [14]. The author used a Kaggle data set that was made accessible to the public. This work uses an SVM classifier to achieve 88% to 89% accuracy in classifying pictures as severe Diabetic Retinopathy, moderate Diabetic Retinopathy, and non- Diabetic Retinopathy. This model's drawback is that it can only categorize Diabetic Retinopathy into three groups. Additionally, overfitting will occur if the model is trained on little amount of data.

For the purpose of identify diabetic retinopathy and glaucoma, Krishna Prasad developed a model that uses a CNN with five layers to find many eye disorders [15]. They developed a real-time implementation with a graphical user interface (GUI) that forecasts the disease with a particular confidence percentage and obtained 80% accuracy in identifying both diseases.

III. Materials and Methods

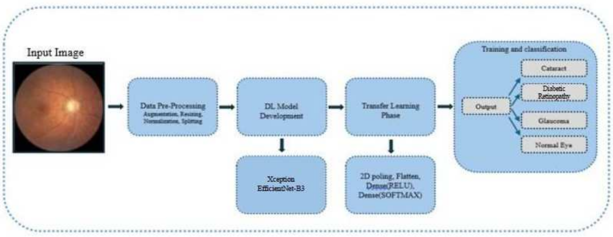


Figure 1: A flowchart that provides an overview of this study process.

The study showed, we investigate Eye Diseases identification and categorization with the use of the transfer learning methodology. The flowchart (Fig. 1) provides a visual representation of the entire work. The process's sequential steps are described in detail in the flowchart. This strategy provides a specific way to recognize and classify Eye Diseases. We progressively provide a complete explanation of the process in the parts that follow.

A. Data Acquisition

This study made use of the Retinal images collection. The dataset that is accessible to the public was obtained from the Kaggle website. This collection contains images of cataract, diabetic retinopathy, glaucoma and normal eye. Because the database had superb quality, cleaned data, it was perfect for DL. 4200 images were taken out of the dataset. In Fig. 2, images are shown as examples. For every evaluation, training, and validation set, there are four different sorts of images: cataract, diabetic retinopathy, glaucoma and normal. Validation, testing, and training sets of data were used to evaluate the categorization model.

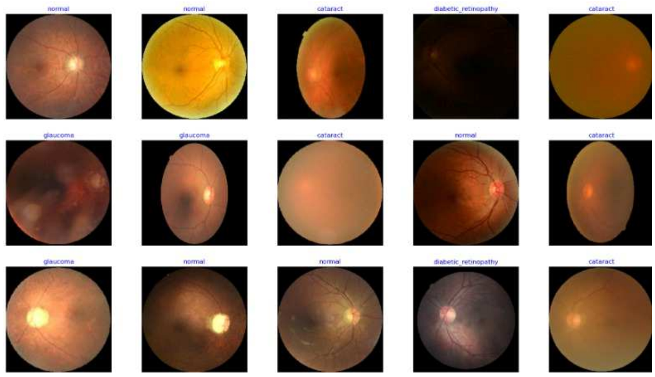


Figure 2: Four types of images: (a) Glaucoma, (b) Normal, (c) Diabetic Retinopathy, (d) Cataract

B. Dataset Split

To aid in the construction and assessment of the model, the data set is divided into subsets for training, validation, and testing. Divide the data set into training, validation, and testing sets at a ratio of 70%:15%:15%. This produces 640 photos for validation, 639 photos for testing, and 5121 photos for training.

C. Data Augmentation

Use data augmentation skills to enhance the data set and strengthen the resilience of the sample. Techniques like rotating, flipping, and zooming are all feasible. All those photos are scaled to 224 × 224 pixels for pre-trained models. We applied the data normalization technique to fit the models.

D. Deep Learning Models

We employ Xception, EfficientNetB3, and three other popular DL architectures for feature extraction and classification. The aforementioned architectures were selected due to their proven performance in many computer vision applications and their relevance to our work on the prediction of eye diseases. The following architectures were employed:

Xception: The inventor of the Keras deep learning framework, François Chollet, created the convolutional neural network architecture known as Xception. "Extreme Inception," or "Xception," is a development of the Inception architecture that adds depth wise separable convolutions. Proposed model is made up of 36 convolutional layers arranged into entry flow, middle flow and exit flow sections that serve as the network's foundation for feature extraction. By effectively merging depth wise and pointwise convolutions, Xception is made to optimize performance by lowering computation costs and parameter counts while increasing precision.

Xception is a popular option for a variety of picture classification tasks, including medical image analysis, because to its strong performance and ease of use. Xception may be trained on retinal imaging data to find patterns and characteristics suggestive of eye illness in the context of disease detection. The method is an efficient tool for early identification and diagnosis of eye disease and may help create more potent therapies and interventions due to its capacity to learn intricate aspects from imaging data.

EfficientNet-B3: A convolutional neural network variation of the EfficientNet family is called EfficientNet-B3. EfficientNet models scale the depth, breadth, and resolution of the network in an ethical way to provide state-of-the-art accuracy while being computationally efficient. With its unique scaling parameters, EfficientNetB3 offers a performance-to-size trade-off that is well-balanced, which makes it is a great option for a variety of image classification tasks.

EfficientNet-B3 has demonstrated excellent performance in several fields, including medical imaging. This architecture may be used to analyze retinal imaging data and find patterns that indicate different eye states in order to detect eye diseases. These patterns could include alterations in retinal morphology, lesions, or structural anomalies linked to conditions including glaucoma, age-related macular degeneration, or diabetic retinopathy. EfficientNetB-3's efficiency allows for faster training and inference, making it particularly effective for large-scale medical imaging datasets. Its capacity to extract intricate information from retinal pictures can help with early diagnosis and detection, which may improve patient outcomes by allowing for prompt intervention and treatment.

Transfer learning: Transfer learning in image classification is predicated on the notion that a neural network learns best when provided with a large and diverse dataset, like ImageNet. This allows the network to adapt to and perform exceptionally well in a specific target task, even though the target task has fewer labelled instances than the pre-training dataset. Using these acquired feature maps is better than starting from scratch with a large dataset and building a large architecture.

Two methods will be used in this study to improve the already trained models: (1) Feature extraction is the process of extracting relevant characteristics from the destination task using features found in the primary task. A new classifier with the possibility to train from scratch was built on top of the pre-trained network in order to modify the feature mappings acquired from the sample data.

Some of the base network's previously frozen layers are unfrozen in step two, the fine-tuning procedure, enabling training of these unfrozen layers in tandem with the recently added classifier layers. The higher-level feature representations of the base network are improved through this fine-tuning process so that they more closely match the intended goal.

E. Model Training

A stochastic gradient descent optimizer with a categorical cross entropy loss function is used to train the models. Rotation, scaling, and flipping are examples of data augmentation techniques that we use to improve model generalization and prevent overfitting.

Use 40 batches, 20 epochs, and a 0.001 learning rate to train each model. We created an image size of 224 x 224 x 3 for every pre-trained model. The Tesla T4 GPU was utilized to train on the Google Colab platform. With 40 batch sizes and 100 epochs, the multi-categorical classification was used. An open-source machine learning framework called TensorFlow was used to implement the pre-trained deep CNN models.

IV. RESULT AND DISCUSSION

The accuracy was classified into three categories: train, test, and validation. Equation 1-4 calculates accuracy, precision, recall, and f1-score. TP, TN, FP, and FN are the symbols that represent True Positive, True Negative, False Positive, and False Negative, respectively.

$$\text{Accuracy} = \frac{\sum TP+\sum TN}{\sum TP+\sum TN+\sum FP+\sum FN} \quad (1)$$

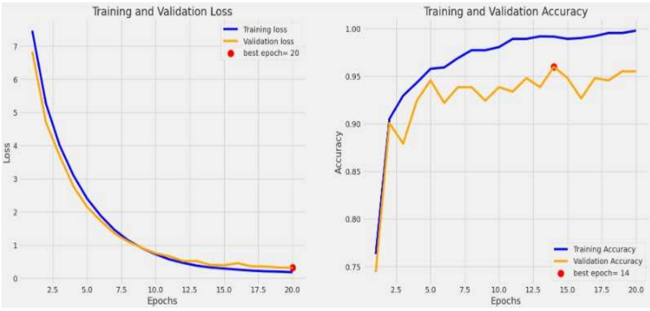
$$\text{Precision} = \frac{\sum TP}{\sum TP+\sum FP} \quad (2)$$

$$\text{Recall} = \frac{\sum TP}{\sum TP+\sum FN} \quad (3)$$

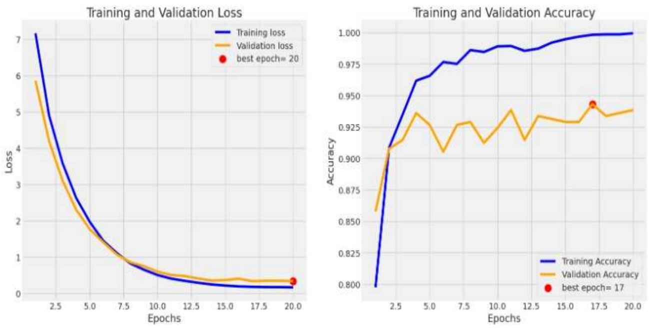
$$\text{F1- score} = \frac{2\sum TP}{2\sum TP+\sum FP+\sum FN} \quad (4)$$

According to Table I, Xception and EfficientNet-B3 both attained training accuracy levels of almost 100% and validation accuracy levels of over 94%. Xception achieved a test accuracy of 92%, whereas EfficientNet-B3 showed a 94% accuracy rate. This is the most noteworthy finding.

The accuracy and loss graph of the Xception model is presented in Figure 3(a). Accuracy in training, validation, and tests is 95%, 92%, and 99.97%, correspondingly. The test loss is 0.40, while the training and validation losses are 0.15 and 0.31. The red dot represents the optimal epoch point, which has an accuracy of greater than 0.95. The loss and accuracy graph for the EfficientNet-B3 model is presented in Figure 3(b). For training, testing, and validation, the corresponding percentages are 100%, 94%, and 94%, respectively. The validation loss in this graph is 0.14, but the training and test losses are both 0.33. The best epoch point, where an accuracy of in excess of 0.92 is represented by the red dot.



(a)



(b)

models
Figure 3: Accuracy and loss graphs for (a) Xception and (b) EfficientNet-B3

TABLE I. COMPARATIVE ANALYSIS OF TWO DIFFERENT MODELS

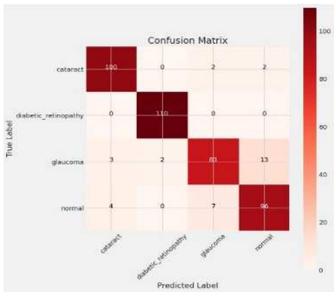
Model	**Train Loss**	**Valid Loss**	**Test Loss**	**Train Acc**	**Valid Acc**	**Test Acc**
Xception	0.15	0.31	0.40	99.97 %	95%	92%
EfficientNet-B3	0.14	0.33	0.33	100%	94%	94%

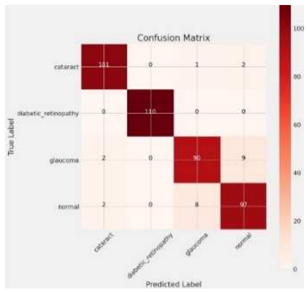
Table II displays the models' test phase performance for each class. F1-score, recall, and precision were employed in the performance classification process. Following the test phase, Figure 4 displays the confusion matrix for Xception and EfficientNet-B3. The confusion matrix from the EfficientNet-B3 model is on the right side, and the one that is from the model used by Xception is on the left side.

The above dialogues demonstrate that both models are running with maximum accuracy. During training, both models showcase nearly 100% accuracy. The EfficientNet-B3 model achieves 94% accuracy in both testing and validation, compared to 92% accuracy in testing and 95% accuracy in validation for the Xception model. Every method of transfer learning might be useful for detection. Our approach to diagnosing eye disease is compatible with these two models, which have been recommended for use.

TABLE II. THE PERFORMANCE OF TWO DISTINCT MODELS

Models	Classes	Precision	Recall	F1-score
Xception	Cataract	0.93	0.96	0.95
	Diabetic Retinopathy	0.98	1.00	0.99
	Glaucoma	0.90	0.82	0.86
	Normal	0.86	0.90	0.88
EfficientNet-B3	Cataract	0.96	0.97	0.97
	Diabetic Retinopathy	1.00	1.00	1.00
	Glaucoma	0.91	0.89	0.90
	Normal	0.90	0.91	0.90





(a) (b)

Figure 4: Confusion matrices for (a) Xception and (b) EfficientNet-B3

V. CONCLUSION

Seeing is believing, and our eyes are some of the most vital organs for experiencing the world. Vision loss has a major impact on well-being, and eye health can even signal underlying health issues. Because of limited access to eye doctors and eye care services, many people might remain unaware of potentially serious health issues. However, the development of deep learning and image processing may be of great assistance in the identification and treatment of eye illnesses. The effectiveness of the Xception and EfficientNet-B3 models for transfer learning-based Eye Disease detection is thoroughly examined in our work. By carefully conducting experiments and analyzing the results, we gained a deep understanding of how well each model performs in this essential field of medical imaging. We identified both their strengths and weaknesses. Across all two models, we observed commendable performance metrics, including high accuracy, precision, recall and F1-score. These results affirm the viability of leveraging advanced neural network architectures for aiding in early Eye disease diagnosis and prognosis. In addition, our comparative study revealed subtle differences between the models. Better accuracy and computational efficiency were shown by EffectiveNet-B3 (95%) and Xception (95%). This demonstrates the significance of model architecture selection and scalability in optimizing Eye Disease detection frameworks.

VI. FUTURE WORK

Several future initiatives to further progress this study and its applications can be contemplated, based on the outcomes of our work. Here are a few schemes:

Future studies will concentrate on improving the classification accuracy of eye illnesses by either improving the current models or introducing more sophisticated deep learning techniques. The study's dataset will be expanded to cover a greater variety of eye disorders, which should enhance the model's capacity to correctly categorize various eye disorders. We also want to integrate other types of data such as genetic information, clinical history, and cognitive test scores to create a more holistic diagnostic model. Additionally, carry out pilot experiments in clinical settings to assess the models' applicability and efficacy in assisting with Eye disease diagnosis. We aim to develop visualization tools/apps by highlighting regions of the eye image that are most symptomatic of eye disease, assist doctors in understanding how the models are making judgments. Actually, our goal is to work with clinicians to create a feedback system so that the models may be continuously improved based on their feedback and actual performance.

VII. ACKNOWLEDGMENT

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