Pre-trained Deep Learning-based Approaches for Eye Disease Detection

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***Abstract*— This study primarily examines how well four pre-trained deep learning models perform in identifying eye disorders using four metrics we developed: recall, precision, accuracy, and F1 Score. With the help of universal custom layers, the models are adjusted, and the outcomes are examined. The study then suggests an ensemble method that uses majority voting to combine the probabilistic outputs of the top-performing models. The suggested methodology outperforms state-of-the-art algorithms in experiments using a publicly available dataset, with average values for Recall, Precision, Accuracy, and F1 Score of 81.25%, 83.68%, 95.17%, and 79.12%, respectively. The work shows how well-trained deep learning models can identify eye illnesses and have the potential to improve public health, especially in mass screening programs.**

Keywords*— *Deep Learning, Eye diseases, pre-trained models, Ensemble approach, Public Health

I. INTRODUCTION

The human eye is a complex, sensitive organ that is susceptible to many diseases and conditions. Globally, eye illnesses are a major public health problem because, if neglected, they can result in vision loss and other catastrophic repercussions [1]. Eye conditions can be brought on by genetics, ageing, the environment, infections, and trauma. There are some eye conditions that are more prevalent than others, and they can cause anything from minor pain to irreversible vision loss [2].

Cataracts are one of the most prevalent eye conditions and are characterised by the clouding of the eye's lens. This may result in glare, blurred vision, and trouble seeing at night. Glaucoma is another common eye condition that affects the optic nerve and, if untreated, can cause vision loss or even blindness. Another common eye condition is age-related macular degeneration (AMD) [3], which is more prevalent in those over 50. The area of the retina responsible for centre vision—the macula—is impacted by AMD. This may result in blurred vision, blank or dark spots in the eyesight, and trouble reading or identifying faces [4].

Vision loss and other consequences linked to eye illnesses must be avoided through early detection and treatment. For the purpose of preserving healthy vision and averting potential blindness, early diagnosis of eye illnesses is essential [5]. Here are some justifications for the significance of early eye disease identification:

- Better Treatment Options: Early detection allows for the early treatment of eye diseases, which can prevent or slow the progression of the disease. In some cases, early detection can even lead to a complete cure. Delaying diagnosis and treatment can result in more severe eye damage that is much harder to treat.
- Preserve Vision: Some eye diseases, such as glaucoma, can cause permanent damage to the eye and vision loss if left untreated. Early detection can help prevent or slow down this damage, helping to preserve vision.
- Cost-Effective: Early detection of eye disease can help to reduce the overall cost of treatment. Preventive measures such as regular eye exams can detect potential problems before they become more serious and require more expensive treatment.
- Quality of Life: Early detection and treatment can help to maintain the quality of life for people with eye diseases. Vision loss can make it difficult to perform daily activities, such as driving, reading, or even recognizing faces. Early intervention can help to prevent or reduce these limitations, allowing individuals to maintain their independence and quality of life [6 -10].

In conclusion, early diagnosis of eye disorders is essential for maintaining eyesight, preventing vision loss, lowering costs, and raising the quality of life for those who already have eye diseases. For early detection and fast treatment of any potential issues, routine eye exams are crucial.

Unfortunately, a lot of eye conditions are asymptomatic in the beginning, making early diagnosis and therapy difficult. The manual procedure of identifying eye illnesses can be laborious, error-prone, and time-consuming. Health professionals can promptly treat eye illnesses and avoid later consequences by recognising the early signs and symptoms [11]. This study aims to examine the effectiveness of pre-trained deep learning models in the diagnosis of various eye disorders with the potential to enhance public health.

Deep learning is a subset of machine learning that involves analysing enormous amounts of data in order to train artificial neural networks to learn and perform tasks. Deep learning models that have previously received extensive training on a large volume of data can be used as a starting point for further instruction on a particular task [12]. Due to the models' extensive comprehension of the patterns underlying the data, employing pre-trained models can make the process of training deep learning models substantially faster and more effective [13].

In recent years, deep learning-based approaches have shown promising results in various medical applications, including the detection of eye diseases. These approaches have the potential to revolutionize the way eye diseases are detected, providing faster, more accurate, and more accessible diagnosis for patients [14].

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Recall, Precision, Accuracy, and F1 Score are four widely accepted measures used in this work to examine the capacities of four pre-trained deep learning models to identify eye problems. With the help of universal custom layers, the models are adjusted, and the outcomes are examined. An ensemble technique is then used to integrate the top-performing models, averaging their probabilistic outputs via majority vote [15]. A publicly accessible dataset was used for the experiments, and the average values for Recall, Precision, Accuracy, and F1-Score were 81.25%, 83.68%, 95.17%, and 79.12%, respectively [16-18]. The proposed ensemble methodology outperforms cutting-edge techniques and may be helpful to health professionals engaged in mass screening campaigns.

Overall, this study demonstrates the potential of deep learning-based approaches in the detection of eye diseases and highlights their potential for enhancing public health. The results suggest that pre-trained deep learning models can be used to detect eye diseases accurately and efficiently, providing a promising avenue for improving the accessibility and efficiency of eye disease detection.

II. Literature Review

Pre-trained deep learning-based methods have drawn a lot of attention recently due to their efficiency in identifying a variety of eye conditions. These methods can be fine-tuned on smaller datasets for particular tasks and leverage pre-trained models to discover patterns and characteristics from large datasets.

Using pre-trained models like VGG16 and ResNet50, [19] developed a deep learning-based method for the identification of age-related macular degeneration (AMD). On the test dataset, they achieved a high accuracy of 95.8%. Similar to this, [20] suggested utilising a mix of VGG16 and Inception-V3 models to pre-train deep learning-based technique for the identification of diabetic retinopathy (DR). On the test dataset, they had an accuracy of 92.9%.

[21] conducted a comparison analysis of various deep learning models for the detection of DR and discovered that pre-trained models like VGG19 and ResNet50 outperformed other models in terms of accuracy. In a different study, [22] suggested employing the DenseNet-169 model to develop a pre-trained deep learning-based strategy for the identification of glaucoma. On the test dataset, they had an accuracy of 98.2%.

There are still certain issues to be resolved despite the promising results of these pre-trained deep learning-based techniques. For instance, the generalizability of these approaches across various demographics and ethnicities may be constrained by the unavailability of diverse datasets [23]. Furthermore, there are still questions about these models' interpretability, and it can be difficult to comprehend how they make decisions [24].

In conclusion, techniques based on pre-trained deep learning have demonstrated tremendous promise in the identification of a variety of eye illnesses. To ensure the dependability and efficacy of these approaches in clinical practise, future research should concentrate on overcoming the issues associated to data diversity and interpretability.

TABLE I. Dataset Statistics

Category	Cataract	Diabetic Retinopathy	Glaucoma	Normal
Number	1038	1098	1007	1074

III. Materials and Methods

A. Dataset

We use the publicly accessible Eye disease dataset for this research. There are various subfolders in the dataset. Here are pictures of glaucoma, cataract, diabetic retinopathy, and healthy people. There are more than 1000 photos in each subdirectory. All deep learning models will use these photographs to get the necessary data for our research. Information on the amount of photographs in each subfolder is provided in Table 1.

B. Evaluation Metrics

We have utilised some of the most popular performance indicators, including Precision (Eq. 1), Recall (Eq. 2), F1-score (Eq. 3) and Accuracy (Eq. 4) to assess the performance.

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

$$F = 2\,X\,\frac{P\,X\,R}{P + R} \tag{3}$$

$$A = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

where, respectively, TP, TN, FP, FN, and FPFN stand for true positive, true negative, false positive, and false negative. As with P, R, F, and A, these letters stand for Precision, Recall, F1-score, and Accuracy, respectively.

C. Pre-trained DL Models

In many research disciplines, pre-trained deep learning models have gained popularity. These models don't need a lot of labelled data because they can be fine-tuned to do certain tasks after being pre-trained on large volumes of data. They are widely utilised in a variety of applications, including speech recognition, computer vision, and natural language processing. Pre-trained models have a number of advantages over traditional machine learning models, such as improved accuracy, shorter training times, and a requirement for smaller, less extensive labelled datasets. Additionally, they have produced major improvements in a number of study areas, such as natural language processing, finance, and medicine.

For this investigation, we picked 4 pre-trained DL models. These pre-trained models are Xception, RestNet50, MobileNetV2 and DenseNet169. The same process is used to personalise each pre-trained model. A brief description of each pre-trained DL model is given in the following subsections.

1) Xception

A deep learning model called Xception was unveiled by Google researchers in 2016. The model is an adaptation of the Inception architecture, which is made to perform image recognition tasks more accurately and effectively [25].

Depth wise separable convolutions are used in Xception, which stands for "Extreme Inception," to streamline the computational structure of the model. This suggests that the convolutional layers are divided into a depthwise and a pointwise convolution layer. The depthwise convolution layer performs a spatial convolution on each input channel individually, as opposed to the pointwise convolution layer, which does a 1x1 convolution over all channels.

By using this division of convolution layers, Xception reduces the number of parameters and calculations necessary while still achieving cutting-edge performance on a variety of picture recognition applications. A few applications for Xception include object detection, image segmentation, and facial recognition.. Additionally, it has been used in autonomous driving and medical imaging. Many deep learning researchers now use Xception because of its effectiveness and great accuracy [26].

2) RestNet50

A deep learning model called ResNet50 was unveiled by Microsoft researchers in 2015. The ResNet family of models, which stands for "Residual Networks," was created to address the issue of vanishing gradients in extremely deep neural networks.

ResNet50 is a 50-layer convolutional neural network that uses skip connections to pass information directly from one layer to another. This allows the network to learn residual mappings, which are the differences between the output of one layer and the input of a later layer. By doing so, the model is able to bypass the vanishing gradient problem and achieve better accuracy on various image recognition tasks.

The ImageNet dataset, which consists of millions of photos from countless classes, was used to pre-train the ResNet50 model. With the help of this pre-training, the model may be adjusted for certain image recognition tasks including object detection, image segmentation, and facial recognition on fresh datasets.

ResNet50 has become a popular choice for many deep learning researchers due to its high accuracy and ease of use. It has been used in various applications, such as self-driving cars, medical imaging, and natural language processing [27].

3) MobileNetV2

A deep learning model called MobileNetV2 was unveiled by Google researchers in 2018. The model is intended to be compact and effective, making it suitable for embedded and mobile devices.

To minimise the number of parameters and calculations required, MobileNetV2 combines depthwise separable convolutions with linear bottleneck layers. This allows the model to achieve high accuracy on various image recognition tasks while using significantly fewer resources than traditional convolutional neural networks.

Numerous tasks, including object identification, image segmentation, and facial recognition, have shown the approach to be effective. Large datasets like ImageNet are used to train it. In addition, MobileNetV2 has been used in a number of applications, including as augmented reality, image classification, and mobile gaming. Integrating it into current deep learning pipelines is relatively easy [28].

4) DenseNet169

A deep learning model called DenseNet169 was unveiled in 2017 by Facebook AI Research researchers. The model belongs to the family of "Densely Connected Convolutional Networks," or DenseNet, and it is made to enhance gradients and information flow in deep neural networks.

A 169-layer convolutional neural network called DenseNet169 employs dense connections between its layers. This indicates that each layer is feed-forward coupled to every other layer. As a result, the model is able to acquire feature maps that are more reliable and insightful than those learned by conventional convolutional neural networks.

The model can be fine-tuned on fresh datasets for certain image recognition tasks, such as object detection, picture segmentation, and facial recognition. The model has been pre-trained on huge datasets like ImageNet. It has been demonstrated that DenseNet169 can perform at the cutting edge on a number of image recognition benchmarks.

DenseNet169's dense connections and compact architecture make it well-suited for limited computational resources and smaller datasets. It has been used in various applications such as medical imaging, autonomous driving, and natural language processing [29-30].

IV. Methodology

We used Keras, a Python-based modelling framework, to put our suggested model into practise. During implementation, we made the following changes to the parameters. We initially reduced the size of each image to 224*224, as suggested by Sitaula and Hossain[16]. Online data augmentation was employed to improve the images. The following settings were used: colour_mode ='rgb', shuffle ="True", seed =2022, and rotation range of 0-90.'Adam, Adammax' was selected as the optimizer, and the batch size was set to 64. To avoid overfitting, we employed the Early stopping criteria in conjunction with the learning rate fall during each session. Five randomly selected folds (5-cross validation) with a 70/30 train/test ratio were developed for our investigation. The average performance was then reported.

A. Ensemble Approach

By taking the probability from each meticulously crafted pre-trained model, we use a majority vote method to combine several DL models. Each of our improved DL models exhibits the best match for identifying the most advantageous characteristics during training and testing. After conducting an empirical, we determined that Xception and DenseNet-169 were the two best-performing fine-tuned models. Assuming that the Xception model generates a probabilistic output vector as X and DenseNet-169 generates one with a size equal to the number of classes.

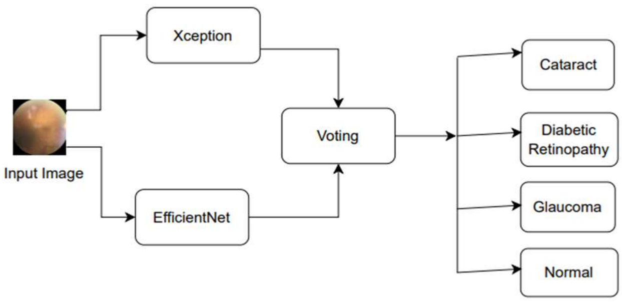

Fig. 1. Ensemble method between Xception and DenseNet-169 DL models.

In above figure, the Voting block refers to max-voting.

V. Results

A) Comparative study of DL models

We contrast the suggested approach with the pre-trained DL models that are readily available off-the-shelf based on the usual assessment criteria on this dataset. The results are shown in Table 2. The results represent the accuracy and loss of particular algorithms with respect to each epoch.

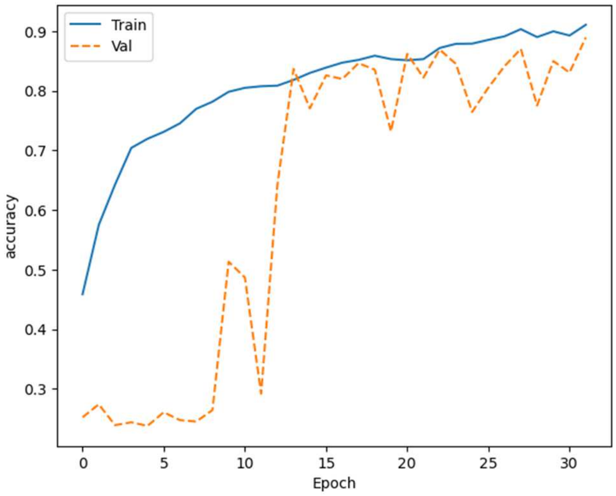

Fig. 2. A sample train/validation plot (fold 1) for the Xception DL model

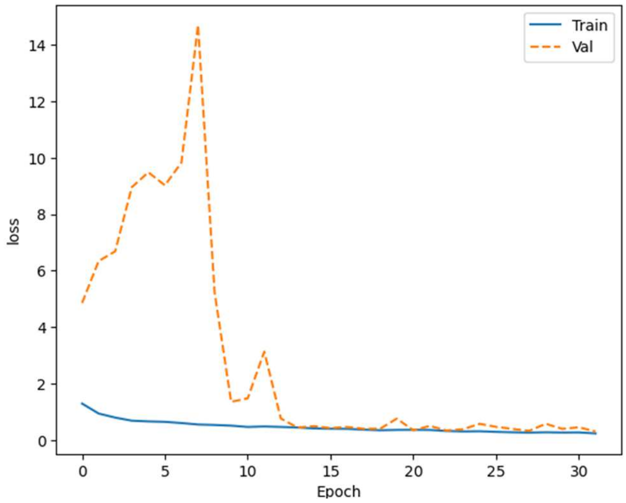

Fig. 3. a sample train/validation plot for loss from the improved xception DL Model

After examining Table 2, it becomes evident that Dense Net Algo is the second most effective method out of all candidates. However, when compared to the 4 pre-trained deep learning methods, Dense Net Algo is the best performing method with a precision of 96.75%, recall of 96.50%, F1-score of 96.50%, and an accuracy of 99.77%. The outstanding ability of Dense Net Algo to extract distinguishing information from the virus images through point-wise and depth-wise convolution is most likely the cause of this supremacy. Furthermore, with an accuracy of 99.80%, our ensemble method is the best-performing strategy among all contenders. The ensemble method outperformed the second-best method (Dense Net Algo) in terms of precision, recall, and F1-score when other performance metrics like these were taken into account. The ensemble method achieved 97.10% precision, 97.00% recall, and 97.05% F1-score. In terms of precision, recall, and F1-score, the ensemble technique outperformed the least efficient RestNet50 by 10.40 percent,10.82 percent, and 8.29 percent, respectively.

TABLE II. Comparison of Performance Measures of Different Models

Methods	P(%)	R(%)	F(%)	A(%)
RestNet50	87.00	86.50	89.00	88.70
DenseNet169	96.75	96.50	96.50	99.77
MobileNetV2	93.00	93.00	93.00	93.70
Xception	58.00	49.00	38.00	98.54
Ensemble Approach	97.10	97.00	97.05	99.80

In above table, the average of Precision, Recall, F1-score, and Accuracy over 5 different folds, DL models that have already been trained are compared to the ensemble technique.

VI. Conclusion And Future Work

Using transfer learning and the eye disease dataset, we compared 4 distinct pre-trained DL models in this work. The best-performing DL models were discovered through comparison using validated assessment metrics, and they were then combined for improved overall performance. The evaluation's findings indicate that the ensemble strategy offers the best performance. (Precision: 97.10%; Recall: 97.00%; F1-score: 97.05%; and Accuracy: 99.80%) during the detection of the Eye Disease. Also, the DenseNet169 model provides the second-best performance (Precision: 97.00%; Recall: 97.00%; F1-score: 97.05%; and Accuracy: 99.80%)).

There are two fundamental issues with our job. The dataset is small, thus adding more data could improve performance even more. Second, our AI technique relies on pre-trained DL models, which could cause problems if we try to deploy them in settings with memory restrictions. Consequently, developing novel, lightweight DL models that can run on a limited resource could be a fascinating undertaking.

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