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Article

Eye Disease Prediction based on Deep learning Approaches

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Abstract: Glaucoma (GC), diabetic retinopathy (DR), and cataracts are the leading causes of vision loss globally. However, the diseases can be prevented from further progression when detected in the early stages. Conventional manual diagnosis is prolonged and requires the experience of a trained ophthalmologist. Therefore, automated techniques using artificial intelligence algorithms are evaluated for their ability to identify these eye diseases. In this study, transfer learning and image augmentation techniques are employed using pre-trained deep-learning (DL) neural network (EfficientNetB3). The model tested based on public available dataset known as from Kaggle repository. The model attained an accuracy of 95%. The knowledge from this study has the potential to aid, hasten, and improve accuracy in the process of eye disease prediction.
Keywords: Data augmentation, Eye disease, deep learning, Data mining, efficient Net.

1. INTRODUCTION

Worldwide, from 1990 to 2020, the age-standardized prevalence of blindness among adults 50 years or older dropped by 28.5% and mild vision impairment decreased marginally (–0.3%, -0.8 to -0.2); Moderate and severe vision impairments were slightly higher (2.5%, 1.9 to 3.2; Insufficient information was available to find this number for vision impairment resulting from untreated presbyopia. During this time, the number of blind persons rose by 50.6%, while those with moderate to severe vision impairments rose by 91.7%. By 2050, 61.0 million individuals are expected to be blind, 474 million (428–518) to have severe and moderate visual impairments, 360 million (322–400) to have mild visual impairments, and 866 million (629–1150) to have uncorrected presbyopia[1].

Patients with vision issues experience a significantly lower quality of life. Eye problems include diabetes, retinopathy, and glaucoma. In 2013, there were 64.3 million cases of glaucoma worldwide[2]. Early discovery of eye disorders can help with proper treatment or, at the very least, prevent these conditions from progressing. However, it is restricted due to a lack of awareness, a scarcity of ophthalmologists, and hefty consultation fees. Therefore, automated screening is necessary[3].

In recent years, DL in machine learning (ML) has notably influenced various scientific domains. Examples include the expansion of creative images utilizing techniques like Generative Adversarial Networks (GAN) [4], AI-based games such as ATARIS[5] and GO[6] that can outperform human players, the improvement of speech and image recognition, and the ability to learn the relationship between star ratings and review texts for prediction and music[7]. In this work, the dataset if first pre-processed using CALHE, data augmentation, then transfer learning with EfficientNetb3 used for prediction the eye disease as GC, DR, cataracts, and normal.

This paper is organized as problem and data description in section 2, section 3 illustrates Models and Methods, section 4 illustrates results, and conclusion in section 5.

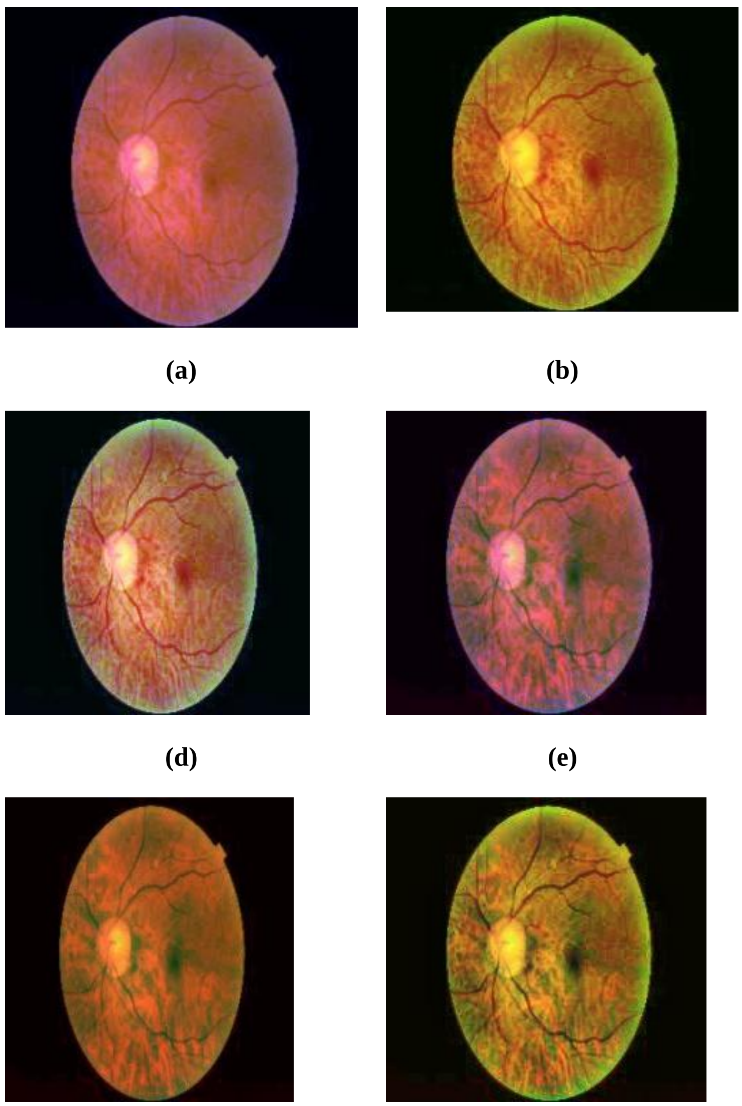
2. PROPLEM STATEMENT

The early diagnosis and treatment of eye problems are crucial since some might lead to vision loss. However, the diseases can be prevented from further progression when detected in the early stages. Conventional manual diagnosis is prolonged and requires the experience of a trained ophthalmologist. Therefore, automated techniques using deep learning methods are evaluated for their ability to identify these eye diseases. Thus, in this study transfer learning with data augmentation and deep learning used for eye disease prediction.

3. MODELS AND METHODS

3.1. Image enhancement

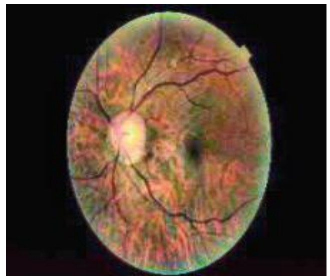
In this paper, Eye disease dataset from Kaggle is used to test the system performance[8]. To achieve a high-quality colour image of the retinal fundus, CLAHE[9] is applied to the R, G, and B channels. As shown in Figure. 1, the highest and clearest feature contrast between other tissues and vessel in the processed image of utilizing CLAHE[9], [10] to G channel. Therefore, all experimental images in this study were processed using CLAHE on the G channel. As a first step, the input RGB image is divided to three channels: R, G, and B. Next, only G channel is used for CLAHE. In this process, the enhanced G channel is combined with the original R and B channels in order to reconstruct an enhanced image. As seen, the vascular contour in the improved image is more visible than in the original image.



(a) **(b)**

(d) **(e)**

(c) (f)



(g)

Figure 1. Improved Image (a)applied to R channel (b) applied to G channel (c) applied to B channel(d) applied to RG channel (e) Applying to RB channel(f) Applying to BG channel(g) Applying to RGB channel(h)Original image.

3.2. Image augmentation

Current image augmentation methods are broadly classified into deep neural network-based black-box and conventional white-box approaches. This section briefly overviews the groupings of techniques that have had the most influence on picture synthesis and augmentation [10].

3.2.1 Traditional transformations

Combining colour alteration with affine image modifications is now the most widely used method for data augmentation. Geometric distortions or deformations are extensively employed as affine transformations for data augmentation, and they are prominently used to increase the number of samples for DL model training (Kwasigroch Arkadiuszand Mikołajczyk, 2017), balance dataset sizes[12], and increase efficiency[13]. However, research is ongoing. Histogram equalization, brightness or contrast enhancement, white balancing, sharpening, and blurring are the most widely used techniques[14].

3.2.2 Adversarial learning-based

The primary goal of image augmentation is to train a task model with a training dataset to obtain adequate generalizability on a testing dataset. The input images that result in a higher training loss are regarded as hard samples, and complex samples are assumed to be more beneficial. Learning an image augmentation approach to produce complex samples from the initial training samples is the goal of adversarial learning-based image augmentation[15]. An early approach[16] looks for a tiny change that maximizes training loss on the augmented samples, where learning optimization determines the ideal magnitude for a specific operation. Assuming that the enhanced image maintains the same label as the original image is one of the primary drawbacks. Designing the type of operation and range of associated magnitude using human knowledge is a frequent technique to meet this assumption. A generative adversarial loss was introduced by[17], to learn a transformation sequence where the discriminator pushes the generated images into original classes rather than unseen or null classes, thereby weakening this assumption.

3.2.3 Texture transfer

The aim of texture transfer is to synthesize a texture from a texture-source image while limiting the semantic content of a content-source image[18]. Applying a given texture to a new image while preserving the original image's visual characteristics, such as contour, shading, lines, strokes, and regions, is challenging. The concept of resampling the texture to a specific content image is the foundation of the majority of traditional texture transfer techniques[19].

3.3. Transfer learning

The idea behind transfer learning for image classification is that a network can efficiently train in the specific target task, which includes fewer labelled instances than the pre-training dataset, if it is usually trained on a large dataset with sufficient data (e.g., ImageNet). These learnt feature maps can be helpful without requiring extensive dataset training for a big model[20]. Taxonomy of transfer learning is demonstrated in figure 2[21].

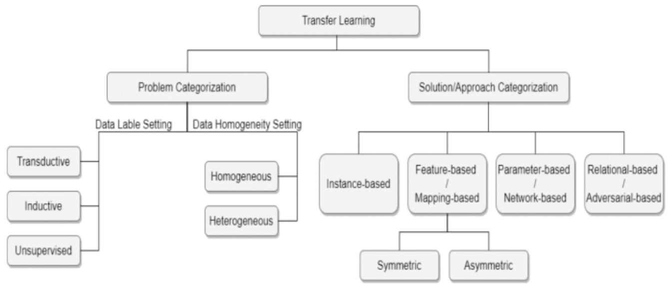


Figure 2. Taxonomy of transfer learning[21].

According to label-setting characteristics, deep transfer learning (DTL) can be classified to three categories: (i) inductive, (ii) unsupervised and (iii) transudative[22]. In a nutshell, transudative learning is when just the source data is labeled; inductive learning is when both the target and source data are labeled; and unsupervised deep transfer learning is when none of the data are labeled[22].

Another classification of DTLS is mentioned and defined by [21], [22] using the applied techniques aspect. They also divided DTLS into four categories: (i) parameter-based/model-based, (ii) mapping-based/ feature-based, (iii) instance-based, and (iv) adversarial-based/ relational-based methods. The foundation of instance-based transfer learning methods is utilizing selected portions of instances (or all) from source data and applying different weighting approaches to target data. In feature-based mapping, instances and features from source and destination data are transformed into more homogeneous data.

3.4. EfficientnetB3

The CNN architecture Efficient Net[23] is available in multiple versions, from EfficientNetB0 to EfficientNetB7. Compound scaling, the foundation of Efficient Net models, balances the convolution network model size to the required size to maximize model accuracy. Compound scaling is a method for uniformly scaling all dimensions using a compound coefficient. This technique enables balanced scaling across the network's width, depth, and resolution.

The underlying model, EfficientNet-B0, was created utilizing a multi-objective neural architecture search to improve floating-point operations and accuracy. EfficientNet is a family of models built on the CNN architecture. For this study, we used EfficientNetB3, which includes the whole family of scales from B1 to B7. In contrast to the conventional arbitrary scaling, the EfficientNetB3 model is a more potent scaling technique based on evenly scaling the depth, breadth, and resolution dimensions in a standard manner. As demonstrated in Eq. (1), compound scaling of the three dimensions is carried out using a set of fixed scaling coefficients, ø. The number of additional computing resources available for model scaling is represented by this compound coefficient[24]. Depth: $d = \alpha^{ø}$, Width: $w = \beta^{ø}$, Resolution: $w = \beta^{ø}$, $=\gamma^{ø}$.

$$\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2, \alpha \geq 1, \beta \geq 1, \gamma \geq 1 \qquad (1)$$

Therefore, the network depth, width, and resolution are increased if the goal is to use computing resources that are 2n times higher. The scaling is based on the idea that larger input images require more network layers to increase the receptive area and channels to ensure more distinct patterns.

3.5. Evaluation metrics

A confusion matrix can be used in binary classification to evaluate the optimal(best) answer. Figure 3 illustrates the confusion matrix[25], [26].

	Actual Positive Class	**Actual Negative Class**
Predicted Positive Class	True positive (*tp*)	False negative (*fn*)
Predicted Negative Class	False positive (*fp*)	True negative (*tn*)

Figure 3. confusion matrix

As equation (2) indicates, the accuracy metric generally calculates the ratio of accurate forecasts to the total number of cases assessed.

$$accuracy = \frac{tp+tn}{tp+tn+fp+fn} \quad (2)$$

4. PROPOSED METHOD

The proposed system main steps are preprocessing using CALHE, image augmentation, and classification with transfer learning. We shall modify pre-trained models-based feature extraction in this study to extract valuable features from the target job. To change the feature maps first learned for the sample, we created a new classifier that can be trained from scratch on top of the pre-trained network. The final layers of the base network and the recently added classifier layers are trained together after fine-tuning and unfreezing a few of the frozen base network's final layers. This allows the base network's higher-order character representations to be "fine-tuned" to suit the intended purpose better. To create an eye disease prediction system, we optimize a CNN network that has already been trained (EfficientNet). Figure 4 illustrates the suggested system.

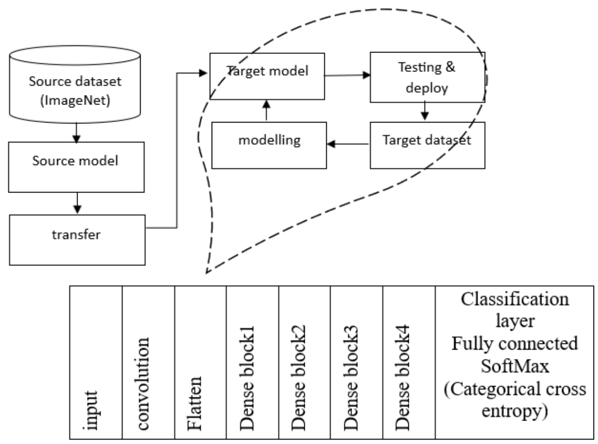


Figure 4. Details of Eyes disease prediction system

5. MATH

In this case, Adam serves as the CNN models' optimizer. Furthermore, the initial learning parameter is set to 0.001, and the batch size to 32. 224 x 224 is the input size. EfficientNet-B3, which is implemented with categorical cross-entropy loss, is one of the baseline approaches. 70% of the total samples are chosen randomly to serve as training samples, with the remaining 30% as test and validation samples.

The pre-trained, effective B3 used in this study was trained and evaluated using extensive ImageNet data, which included a variety of categories like vehicles, animals, flowers, and more. While exhibiting a limitation in their application to specific product sectors, such as medical lesion (DED) detection, the model performs well in object picture classification. Numerous intricate features and the location of lesions in the retinal fundus image determine the prognosis of pathological indications in the photos. Each CNN layer creates a new representation of the input image by gradually extracting the most unique features.

The real-time augmentation ImageDataGenerator class from Keras was used to enrich the imbalanced dataset and reduce the possibility of model overfitting. Pre-trained models were fine-tuned following the removal and retraining of n layers (n was CNN layer-dependent).

The model performance is demonstrated in figure 5, and 6, respectively. And confusion matrix illustrated in figure 7.

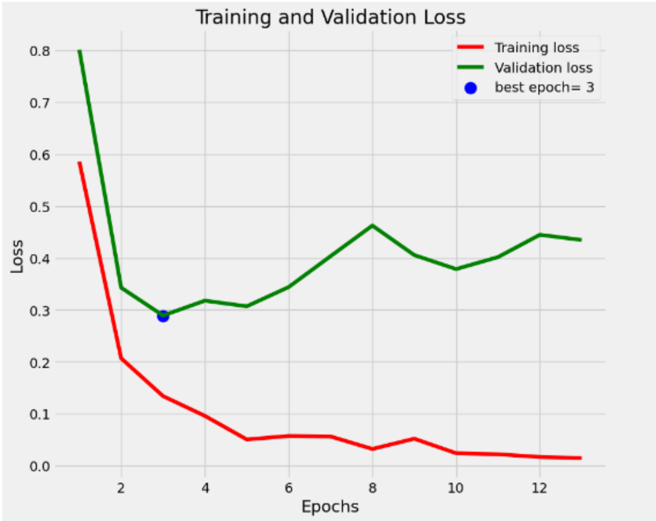


Figure . Training and validation Loss

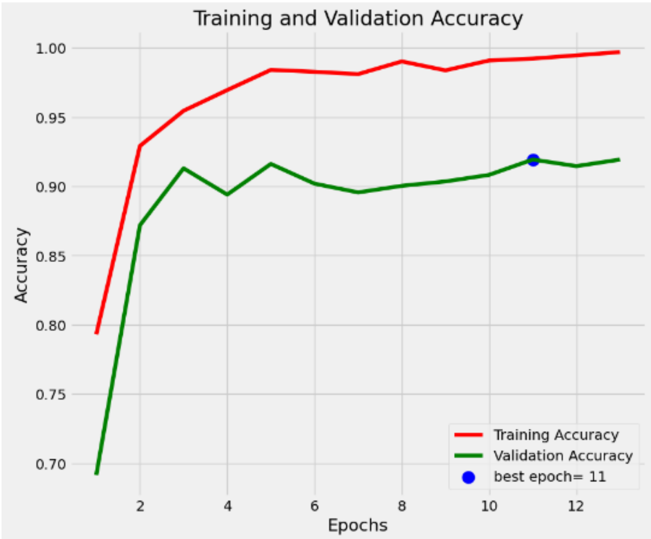


Figure 6. Training and validation accuracy

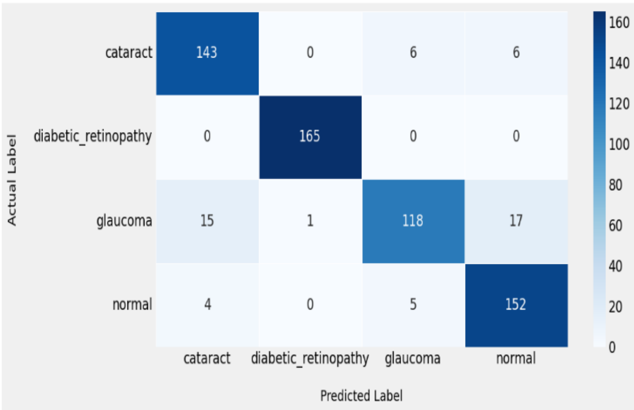


Figure 7. Training and validation accuracy

6. CONCLUSIONS

One of the most vital sense organs in the human body is the eye, and losing vision would significantly negatively impact one's quality of life. Furthermore, the eye may also indicate several hazardous medical conditions. Unfortunately, a dearth of ophthalmologists and access to eye care may mean that many individuals are unaware of these health issues. However, developing deep learning and image processing may greatly aid in identifying and diagnosing many illnesses. This study identified three eye conditions—glaucoma, diabetic retinopathy, and cataracts—using CNN and transfer learning. Although CNN alone is insufficient for categorizing eye conditions, transfer learning greatly improved its effectiveness. Transfer learning moves the CNN model to the EfficientNet B3 pre-trained model.

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