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DEEP LEARNING BASED AUTOMATIC LEFT AND RIGHT EYE IDENTIFICATION FROM COLOR FUNDUS IMAGES

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Abstract

The application of computing intelligence in the field of Ophthalmology is gaining particular interest. Retinal fundus image analysis is one such area that is being explored with computational learning techniques. Automatic Identification of left and right eye in fundus images provides insights into the position of various anatomical structures within the retina and also for diagnosis of retinal diseases grounded on properties of the optic disc. The majority of earlier works attempt to identify the left and right eyes through the segmentation of retinal structures. A few works do not involve segmentation but utilize the entire image for this task. This work attempts to identify the left and right eyes without segmenting structures as well as by providing only three-fourths of the image as input. In this regard, the proposed methodology involves resizing the image into lower resolution, transforming it to L*a*b* colour space, applying CLAHE-based contrast enhancement, converting back to the original colour space, and cropping the image such that only three-fourth of the width is retained, scaling image such that pixel values range between 0 and 1, classification model building through a convolutional neural network built from scratch, performance evaluation through validation set of images and evolving of the best learning model for left and right eye classification in fundus images. The proposed methodology is trained and evaluated through a fundus image dataset available in the public repository of Kaggle. The methodology achieves a validation accuracy of 98.63% on 10906 validation images and test accuracy of 98.63% on 42670 test images. Further, the model is fine-tuned to identify left and right eye images in other retinal fundus benchmark datasets namely HRF, DRIVE, Diaretdb0, Diaretdb1, and HEI-MED available in public repositories. With very little fine-tuning with 40% of images from each dataset as training and 60% of images for testing, a classification accuracy of 100% is achieved for all the datasets.

Keywords: Convolutional Neural Networks, Deep Learning, Computer Vision, Retinal Fundus Images, Left and Right Eye, Classification, Retinal Diseases

1. INTRODUCTION

The utilization of computational intelligence is being explored in many domains, out of which the field of Medicine is among the highest-ranked. The developments in the field of medicine through the application of computational intelligence techniques aid in serving society one step ahead. The incorporation of computational techniques to the field of Ophthalmology in the view to gain new insights is attaining particular interest in the research world. Ophthalmologists investigate various parts of the eye to identify the presence of abnormalities. Among all the anatomical structures within the eye, the retina, the screen at the back of the eye on which the image captured by the eye falls, is examined to identify the majority of sight-threatening eye diseases. The retina can be imaged through many techniques such as fundus photography, optical coherence tomography, and so on [1]. The fundus images acquired through fundus photography expose many retinal anatomical structures namely blood vessels, macula, optic disc,

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and disease structures such as micro aneurysms, exudates, hemorrhages, and cotton-wool spots if present [2]. The color fundus images of the retina can thus be explored to identify many interesting findings such as if the retinal image belongs to the left or right eye if the image characterizes a healthy eye or a diseased eye and the severity of the disease and so on. Left and right eye identification is one of the signification findings that aid in further investigations. Retinal fundus images of the left and right eye appear different owing to the variation in position and direction of the anatomical structures namely optic disc and blood vessels. An illustration of left and right fundus images is provided in Figure 1(a) and Figure 1(b) respectively.

Figure 1: Illustration of (a) left retinal fundus image and (b) right retinal fundus image

(a) (b)

It is noticeable that the optic disc is positioned right to the macula in the right eye and left to the macula in the left eye. Further, it is observable that the central retinal artery and vein converge towards the right in the right fundus image and converge towards the left in the left eye fundus image thereby making the blood vessel pattern different in the left and right eye. Thus, gaining prior information on whether the image under consideration is of a left or right eye shall facilitate a better understanding of the position of other anatomical structures thereby aiding its localization and segmentation. Further, identification of the left or right eye facilitates recognition of ISNT (Inferior, Superior, Nasal, and Temporal) regions which form the basis for the ISNT rule. ISNT rule acts as a thumb rule for differentiating healthy optic discs from abnormal ones. The rule proclaims that the neuro-retinal rim in a healthy optic disc is thickest in the inferior region, diminishes its thickness in the superior region, and nasal region, and is thinnest in the temporal region [3]. In the left and right eyes, the nasal and temporal regions are laterally inverted as the nasal region is at the left side in the optic disc of the left eye and is on the right side in the optic disc of the right eye fundus image. Thus, the automated recognition of the left and right eye enlightens the correct positions of the ISNT regions thereby facilitating the application of the ISNT rule that is widely used for diagnosing Glaucoma and other retinal diseases that ground on characteristics of optic disc for its diagnosis. Furthermore, left and right eye detection aids in annotating the eye under consideration as either left or right in a fully automated retinal image analysis system. Despite having manyfold applications in the field of Ophthalmology, only a few automated computational techniques [4-8] have been put forth in the literature for left and right eye identification from fundus images. This work targets to identify whether the provided fundus image belongs to a right or left eye with three-fouth of the image being given as input to a deep convolutional neural network-based learning model. A brief

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review of the existing works toward left and right eye recognition is presented in the following section.

2. LITERATURE REVIEW

Manually, the left and right eye is identified through the position of the optic disc, macula, and converging pattern of the central retinal artery and vein. Computational techniques are sought for automatic identification of the left and right eyes. The existing approaches toward the left and right eye recognition can be broadly categorized into two groups namely techniques that involve localization and segmentation of retinal anatomical structures and techniques that do not necessitate the segmentation or localization of anatomical structures.

Firstly techniques that involve segmentation and localization of retinal structures such as optic disc, macula, and blood vessels are concisely presented here.

A methodology that considers the position of the optic nerve head with respect to that of the macula has been put forth [4]. In this approach, the optic cup is found through its marked high pixel intensity. Then, a region of interest is derived based on the optic cup as a center. Subsequently, the optic disc is segmented from the region of interest through thresholding and morphology-based image processing techniques. Further, in the segmented optic disc, the sum of pixel intensities of the green channel on the left and right half is computed and based on the half that characterizes higher cumulative pixel intensity, an understanding of which half is the nasal region and which one is temporal region can be made, depending on which the conclusion of the left or right eye can be derived. This approach has attained an accuracy of 92.23% on 194 images obtained from the Singapore Eye Research Institute.

Subsequently, another approach rooted in the properties of retinal structures for the detection of the left and right eye has been advocated [5]. In this methodology, the optic disc, blood vessels within the optic disc, and macula are segmented through image processing techniques. Then, features are extracted from these segmented structures. These features are then fed into support vector machines in order to make a decision on whether the given image belongs to the left or right eye. This methodology has achieved an accuracy of 94.12% on 102 retinal fundus images obtained from hospitals.

Yet another methodology grounded on the orientation of central retinal veins within the optic disc has been proposed [6]. In this approach, the optic disc is initially segmented through an active shape model. Then, the segmented disc region is convolved with local adaptive filters in the view to extract central retinal blood vessels within the optic disc. From the binary map of the extracted retinal vessels, its inclination can be estimated based on which a conclusion of the left or right eye has been made. The methodology identifies the left and right eye correctly in 98% of the 650 images acquired from the Singapore Eye Research Institute.

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Another published research introduces four models for left and right eye identification, out of which two involve localization of optic disc while the other two do not necessitate localization of any retinal structures [7]. The first model attempts to localize the optic disc based on the intuition that it is the brightest region in the fundus image. In this regard, the entire image is divided into 10 * 10 regions and the average pixel intensity of the grayscale image is computed. Then, based on the position of the region (in either half of the image) that characterizes the highest average grayscale pixel intensity, a verdict on left or right wyw can be derived. This technique reaches an accuracy of 93.14% on 1633 images obtained independently. The second model employs a faster R-CNN model for optic disc localization. Based on the position of the optic disc in either half of the fundus image, the left or right eye is finalized. This approach attains an accuracy of 97.67% on the same set of test images.

The third and fourth models do not require the segmentation of retinal structures. The third model is termed the left-right contrastive classification model. This approach divides the image into two vertically bisected sub-images. Then, a 26-dimensional local binary pattern feature vector is elicited for each sub-image. Then, the extracted features are presented to a support vector machine classifier such that it predicts positive and negative labels for each sub-image. If the left sub-image is predicted positive, then the presented fundus image belongs to a left eye or if the right sub-image is predicted positive, then it is concluded as the right eye. This method attains an accuracy of 97.18% on the same set of test images.

The fourth model is based on deep learning. The methodology involves presenting an entire image to the fine-tuned CNN model and deriving softmax probabilities to conclude if it is a left or right eye. In this regard, ResNet-18 is employed and retrained for the task of left and right eye classification. The methodology accomplishes an accuracy of 98.47% on the considered test set images.

Another methodology that is grounded on deep learning has been put forth toward the left and right eye recognition [8]. In this approach, a seven-layer CNN is trained from scratch with 30119 entire fundus images. The optimized model accomplishes an accuracy of 97.4%.

From the literature study, it is realized that identification of left or right eye has been either carried out through position or features of segmented or localized retinal structures namely optic disc, blood vessels within disc and macula, or through providing entire fundus images to deep learning models. Deep learning models involving convolutional neural networks fetch higher performance than their other counterparts. However, an entire fundus image is not needed for training the deep neural networks. In this work, only three-fourths of the fundus image is provided for training a CNN built from scratch. Further, the validation of the methodologies has been done only on a few hundreds or thousands of images. In the current work, around 10000 images have been used for validation and 40000 images have been provided for testing making it more reliable. The model has also been fine-tuned to attain outstanding performance in benchmark retinal datasets available in public repositories. The proposed methodology is presented in the following section.

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3. MATERIALS AND METHODS

The details of the dataset used for validation of the developed algorithms and the methodology adopted for the left and right eye identification is presented in this section.

3.1 Dataset Description

The dataset [9] used for evaluating the processes in the proposed methodology is obtained from Kaggle, a public repository [10]. The dataset comprises a large set of high-resolution images captured under varying imaging conditions. The name of the image itself contains an indication of whether it is a left or right-eye image. (For instance, 21_right.jpeg refers to the right eye image of a patient with ID 21). The dataset comprises 35126 training images, 10906 validation images, and 42670 testing images. In all training, validation, and testing set of images, the number of left and right eye images are equal making it a class-balanced dataset. The dataset characterizes high cardinality of training images, which is a prerequisite for an efficient deep learning process and hence is chosen for training the proposed model. The proposed approach employing deep learning is explained in the following sub-section.

3.2 Proposed Methodology

The proposed methodology involves pre-processing of retinal fundus image through image processing techniques and then presenting it to an optimized deep learning model in order to derive a prediction of whether the provided image belongs to the left or right eye. The proposed methodology is portrayed in Figure 2.

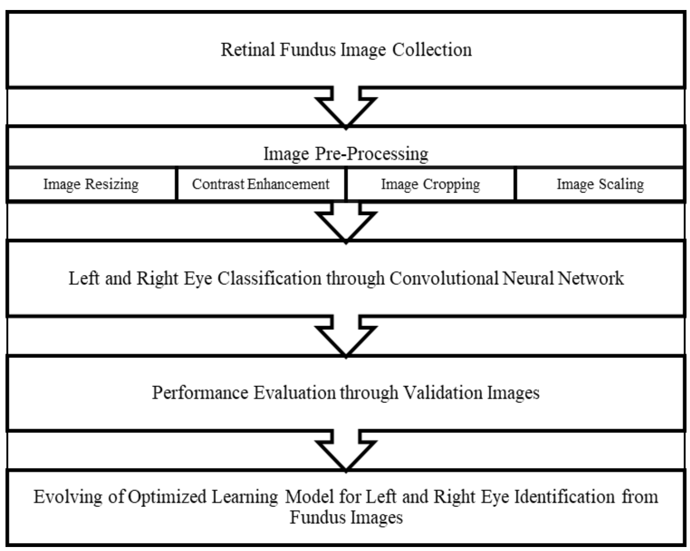

Figure 2: Proposed Framework for Left and Right Eye Identification in Fundus Images

The advantage of the proposed methodology is that it does not involve segmentation of retinal structures and further does not require the entire image to be given as input. The proposed framework comprises of retinal image data collection, image pre-processing, classification through Convolutional neural networks (CNN), performance validation

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through validation set of images, and evolving of the optimized learning model for left and right eye identification in fundus images. The processes involved in the proposed framework are detailed further.

The fundus images are obtained as RGB images. These images are initially resized to 224 * 224 pixels thereby reducing the computational complexity that occurs when dealing with high-resolution images. Then, the images are enhanced by improving their contrast through Contrast Limited Adaptive Histogram Equalization (CLAHE) [11]. In this context, the RGB images are initially transformed into L*a*b* color space that constitutes the L (lightness), a, and B (color opponents) components. Then, the L channel is contrast-enhanced through the CLAHE procedure. In this regard, a clip limit of 2 and a tile size of 8 * 8 have been set. Further after improving the contrast of the L Channel, the images are converted back from L*a*b* color space into RGB color space.

Subsequently, the images are cropped. The entire retinal fundus image is not necessary for the identification of the left or right eye. The optic disc and the inclination of central retinal vessels are sufficient to understand if it is a right or left eye. In order to gain this understanding, only three-fourths of the image is enough. Hence, the images are cropped such that the images are 224 * 168 * 3. This removes 37632 pixels from further processing thereby reducing the computational complexity heavily. Moreover, the methodology is based on deep learning and the reduction in the number of inputs plays a major role in computational overhead. Also, this step acts as a feature selection step as it removes the unnecessary pixels that do not have significance in left and right eye identification and therefore shall aid in improved classification performance.

After cropping, the images are subjected to image scaling. During this process, the pixel values that range between 0 and 255 are transformed to 0 and 1 by dividing all the pixels by 255.

After pre-processing, the pre-processed images in the training dataset are provided as input to the deep learning model, and the model is trained and optimized for left and right eye classification tasks. Among many deep learning architectures, the proposed methodology adopts convolutional neural network (CNN) based architecture. CNN is a type of neural network dedicated to eliciting spatial and significant information from images [12]. It accepts an image as its input and performs various processes and elicits significant information and formulates a feature vector with which the input image is classified into one of the many categories in context.

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The proposed CNN architecture is portrayed in Figure 3.

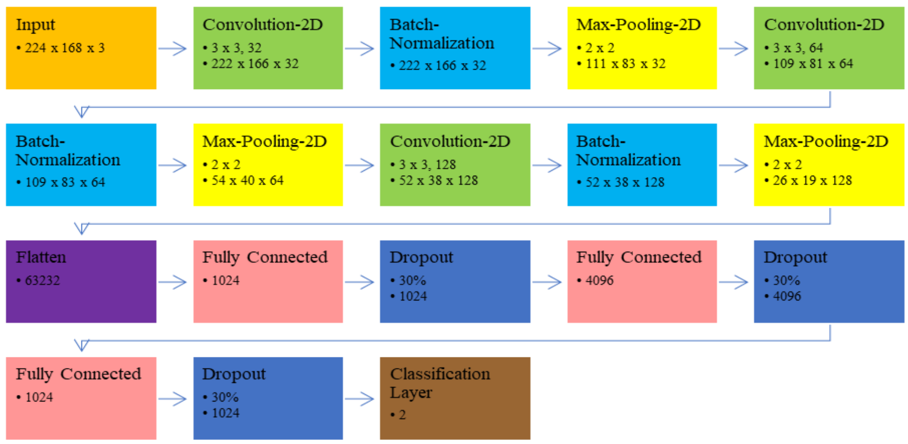

Figure 3: Proposed CNN architecture for Left and Right Eye Identification in Fundus Images

Firstly, the input image is subjected to the first convolutional layer wherein 32 different filters convolve with the image to yield 32 feature maps of size 222 x 166. Each filter characterises a kernel of size 3 x 3, the stride of (1, 1), and padding set to valid. The output feature maps of this layer are then subjected to ReLu activation in the view of introducing non-linearity to the output. Then, the output is subjected to a batch normalization layer that scales the output. The output of the batch normalization layer also characterises a size of 222 x 168 x 32. This output is then presented to a max pooling layer, which is usually incorporated for reducing the dimensionality of the convolved output as well as extracting significant information from it. Here, a pooling layer with a pool size of 2 x 2 is incorporated in the view to yield a put of size 111 x 83 x 32. This output is again given to another convolutional layer wherein 64 different filtering operations are involved yielding an output of size 109 x 81 x 64. This output is again subjected to batch normalization and further to max pooling providing an output of size 54 x 40 x 64. Further, another sequence of the convolutional layer with 128 filters, a batch normalization layer, and a max pooling layer is applied to yield an output of size 26 x 19 x 128. This output is then flattened and projected across three dense fully connected layers of size 1024, 4096, and 1024 with the ReLu activation function. It is to be mentioned that a dropout of 30% is set after each dense layer in order to avoid overfitting. Finally, a classification layer with two neurons activated by the SoftMax activation function is applied to compute probabilities of being left or right eye.

Such a CNN model built from scratch is initialized with random weights and then optimized using an Adam optimizer [13] over many epochs to obtain an optimized deep learning model for left and right eye identification in fundus images. For the purpose of training, a learning rate of 0.001 is set. The rate is dynamically reduced by a factor of 0.5 if there is no improvement in validation accuracy for more than 10 epochs.

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The performance of the model is assessed through the validation accuracy obtained by subjecting the trained model to the validation set of images from the Kaggle dataset. The model (with optimized weights) that yield the highest validation accuracy over the specified number of epochs or the model with the highest validation accuracy after reaching a plateau in performance in terms of validation accuracy is considered the best-evolved model for left and right eye classification.

The performance of the proposed methodology is projected through various experiments. The experiments and the associated results are presented in the following section.

4. RESULTS AND DISCUSSION

Various experiments are performed to evaluate the performance of the proposed methodology. Initially, the classification model is trained with 35126 training images of the Kaggle dataset [9]. Then, the methodology is validated with 10906 images from the validation set, out of which 5453 are left-eye images and the remaining 5453 are right-eye images. The experimental setting that yields the best results for validation images is then used for left and right eye identification in 42670 images from the test set.

Initially, analysis is made on whether a part of the image is sufficient for left and right eye classification or the entire image is required. Secondly, the investigation is made on whether image scaling improves the performance of the classification model. Thirdly, the impact of contrast enhancement is studied by applying two different contrast enhancement strategies to the retinal fundus image. Finally, the effect of the dropout percentage is analysed with respect to the performance of the deep learning model in this context. Some parameters that are kept constant across all the experiments include learning rate = 0.001, the maximum number of epochs = 100, termination if the validation accuracy does not improve over 35 epochs, and model check pointing based on validation accuracy.

4.1 Impact of Fraction of Image as Input

Based on the domain knowledge gathered, it is not necessary to provide the entire image as input to the methodology. Either a half or three-fourths of the image should be sufficient for this task. Experiments are conducted by providing half image (width = 112), three-fourth image (width = 168) and entire image (width = 224) as input to the deep learning model. It is to be mentioned that during these experiments, the images are initially resized to 224 x 224 x 3. But scaling and contrast enhancement are not applied. Further, dropout is set to 30%. Table 1 shows the validation accuracy and cardinality of correct and incorrect predictions for these three experiments with respect to left and right eye classification.

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Table 1: Performance of Proposed Methodology with respect to the varying fraction of input image

Image Fraction	Accuracy	Correct Predictions		Incorrect Predictions	
		L->L	R->R	L->R	R->L
Half	98.32	5360	5363	93	90
Three-Fourth	98.56	5379	5370	74	83
Full	98.36	5371	5356	82	97

* L denotes Left Eye and R indicates Right Eye

Table 1 portrays that the proposed methodology achieves better outcomes when provided with a three-fourths image as input. The methodology achieves a recall and precision of 98.64% and 98.48% for the left eye and 98.48% and 98.68% for right eye images respectively. Further, on investigating, the number of parameters for these three settings, it is derived that the total number of parameters for half, three-fourths and entire images are 49385410, 73240514, and 97095618 respectively. This evidently points out that reducing the input size reduces the number of parameters thereby reducing the computational overhead. The number of parameters involved in the deep learning model when provided with the three-fourth image is 24.57% less than compared to that of providing a full image to the deep learning model. Thus, providing three-fourths of the image reduces computational complexity as well as exhibits improved classification performance on a validation set of images. The same model when presented with 42670 test images yields an accuracy of 98.56%. The model has been able to classify 21012 left eye images correctly as left eye and 21043 right eye images as the right eye. However, it has misclassified 323 left eye fundus images belonging to the right eye and 292 right eye images as belonging to the left eye. Thus, the model achieves a recall, precision, and f1-score of 98.49%, 98.63%, and 98.56% with respect to the left eye and 98.63%, 98.49%, and 98.56% with regard to the right eye respectively. Subsequently, the impact of image scaling is investigated.

4.2 Effect of Image Scaling

Based on the findings from the previous sub-section, further experiments proceed with a three-fourths image as its input. Subsequently, this section analyses if image scaling can enhance the left and right eye classification performance. In this context, the experiment without image scaling has input values in the range of 0 to 255 whereas the trial with image scaling shall have input values between 0 and 1. It is to be mentioned that during these trials, contrast enhancement is not applied. Further, dropout is set to 30%. Table 2 shows the validation accuracy and cardinality of correct and incorrect predictions for these experiments with respect to left and right eye classification.

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Table 2 Impact of Image Scaling with regard to Left and Right Eye Classification

Image Fraction	Accuracy	Correct Predictions		Incorrect Predictions	
		L->L	R->R	L->R	R->L
Without Scaling	98.56	5379	5370	74	83
With Scaling	98.62	5379	5377	74	76

Table 2 exhibits that the proposed methodology reveals better outcomes when provided with a scaled three-fourths image as input. The methodology achieves a recall, precision, and f1-score of 98.64%, 98.61%, and 98.56% for the left eye and 98.64%, 98.61%, and 98.56% for right eye images respectively.

Furthermore, with test images, the methodology incorporating image scaling attains an accuracy of 98.61%. The model has been able to classify 21031 left eye images correctly as left eye and 21045 right eye images as the right eye. However, it has misclassified 304 left eye fundus images belonging to the right eye and 290 right eye images as belonging to the left eye. Thus, the model achieves a recall, precision, and f1-score of 98.58%, 98.64%, and 98.61% with respect to the left eye and 98.64%, 98.58%, and 98.61% with regard to the right eye respectively. Further, the investigation proceeds with analysing the impact of contrast enhancement on the classification performance of left and right eye classification in fundus images.

4.3 Influence of Contrast Enhancement

Based on the results from the previous sub-section, further experiments proceed with a scaled three-fourths image as its input. Subsequently, this sub-section investigates if contrast enhancement of the input image can increase the left and right eye classification performance. In this regard, three trials are performed. The first trial does not involve any contrast enhancement. The second trial incorporates ClAHE contrast enhancement on the green channel of the RGB image. The third trial involves conversion to L*a*b* colour space and then CLAHE on the L channel followed by converting back to RGB colour space. Again, in these experiments, the dropout is set to 30%. Table 3 reports the validation accuracy and cardinality of correct and incorrect predictions for these experiments related to contrast enhancement with respect to left and right eye classification.

Table 3 Influence of Contrast Enhancement with regard to Left and Right Eye Classification

Image Fraction	Accuracy	Correct Predictions		Incorrect Predictions	
		L->L	R->R	L->R	R->L
None	98.62	5379	5377	74	76
Green Channel	98.58	5375	5376	78	77
L Channel	98.65	5384	5375	60	78

Table 3 reveals that the proposed methodology attains better outcomes when provided with a scaled contrast-enhanced (L channel enhancement) three-fourth image as input. The methodology achieves a recall, precision, and f1-score of 98.73%, 98.57%, and

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98.65% for the left eye and 98.57%, 98.73%, and 98.65% for right eye images respectively.

Furthermore, with test images, the methodology incorporating conversion to L*a*b* colour space, L channel contrast enhancement succeeded by RGB conversion, and image scaling attains an accuracy of 98.63%. The model has been able to classify 21042 left eye images correctly as left eye and 21045 right eye images as the right eye. However, it has misclassified 293 left eye fundus images belonging to the right eye and 290 right eye images as belonging to the left eye. Thus, the model achieves a recall, precision, and f1-score of 98.63%, 98.64%, and 98.63% with respect to the left eye and 98.64%, 98.63%, and 98.63% with regard to the right eye respectively. Furthermore, the investigation proceeds with analysing the effect of dropout percentage on the classification performance of left and right eyes in fundus images.

4.4 Impact of Dropout Percentage

With the findings from the previous sub-sections as the basis, further experiments proceed with a scaled L channel contrast-enhanced three-fourths image as its input. This sub-section further examines if increasing or decreasing the dropout percentage enhances the performance of left and right eye identification. In this aspect, the dropout is varied from 10% to 50% in steps of 10%. Table 4 reveals the performance of the proposed methodology toward the left and right eye classification (accuracy and cardinality of right and wrong predictions) on validation set images with regard to various dropouts.

Table 4 Performance of Proposed Methodology with varying Dropouts

Dropout %	Accuracy	Correct Predictions		Incorrect Predictions	
		L->L	R->R	L->R	R->L
10	98.50	5369	5373	84	80
20	98.53	5376	5370	77	83
30	98.65	5384	5375	60	78
40	98.56	5386	5363	67	90
50	98.58	5385	5366	68	87

Table 4 exhibits that the proposed methodology reaches its maximum potential only when the dropout is 30%. Either decreasing or increasing the dropout has not improved the classification performance.

Thus, it can be derived that the methodology achieves its best outcomes when the three-fourth image is provided as input, converted to L*a*b* colour space, subjected to L channel CLAHE enhancement, transformed back to the original colour space, scaled between 0 and 1 and dropout set to 30%.

The plot of training accuracy and validation accuracy over epochs as well as the plot of training loss and validation loss over epochs is projected in Figure5 (a) and (b) respectively.

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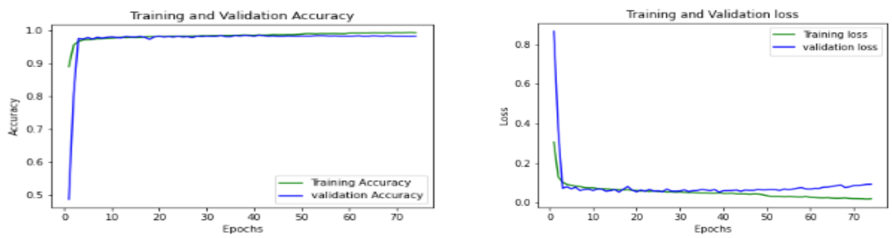
Figure 4: Performance of the proposed methodology (a) Training Accuracy and Validation accuracy over Epochs (b) Training Loss and Validation Loss over Epochs



(a) (b)

The best-evolved model has achieved its maximum validation accuracy at the 40th epoch and the training has completed at the 74th epoch as there has not been any improvement over 35 epochs. In order to train these models for various experiments, Kaggle NVDIA TESLA GPU has been utilised. In such a setting, the models take around 8 minutes for every epoch and hence incur a maximum of 12 hours (minimum 5 ½ hours) for training each model.

Further, with regard to performance comparison with existing works, a private dataset is used in works [4-7] and a random sample of the Kaggle dataset is used in [8]. Hence, a direct comparison with earlier works is not possible. However, the proposed methodology achieves high accuracy performance when presented with large quantities of testing images (more than 40000) when compared to existing methods presenting their results with hundreds and a few thousands of test images.

Further, the best-evolved model is adapted to identify left and right eye images in other benchmarks' retinal fundus image datasets, the details of which are provided in the subsequent sub-section.

4.5 Performance with other benchmark Retinal Datasets

Other retinal fundus image datasets namely HRF [14], Diaretdb0 [15], Diaretdb1 [16], DRIVE [17], and HEI-MED [18] that are available in public repositories are explored for left and right eye identification. Images in each dataset may be acquired from different imaging conditions and hence a slight fine-tuning according to the images in the specific dataset is justifiable. Therefore, the best-evolved model is fixed as the base pre-trained model, and 40% of the images in each dataset are provided as training images in the view to fine-tune the model towards the left and right eye classification for the specific dataset. The remaining 60% of the images are used for testing purposes. The model is fine-tuned for not more than 20 epochs that incur a maximum of 10 minutes in total for each model. The details of the experiments are presented in Table. 5.

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Table 5 Performance of Proposed Methodology on other benchmark retinal datasets

Dataset	# Train	# Test	Maximum Epochs	Accuracy (%)	L->L	R->R
HRF	18	27	3	100	12	15
DIaretDB0	52	78	10	100	39	39
DiaretDB1	35	54	12	100	27	27
Hei-MED	67	102	7	100	17	85
DIVE	16	24	15	100	6	18

As the model has already been trained by 35126 images and the considered datasets have very few numbers of images when compared to that of the original Kaggle dataset, the model achieves 100% left and right eye classification accuracy in all four datasets with very little fine-tuning.

Thus, the proposed methodology can be used to serve Ophthalmologists in real-life scenarios.

5. CONCLUSION AND FUTURE WORK

Computational learning methods are exploited for retinal image analysis. Identification of left and right eye from fundus images despite having many fold applications has been less explored. The existing techniques majorly involve the segmentation of the optic disc, macula, and /or central retinal veins or arteries. A few techniques that do not necessitate the segmentation of these structures provide the entire image for analysis. It is intuitively realised that only half or three-fourth image is sufficient for left and right eye identification. Hence, this work provided only three-fourths image as input, thereby reducing the computational complexity by approximately 25%. Further, the classification accuracy has also improved with a three-fourths image as input when compared to that providing the entire image. Further, the impact of contrast enhancement and image scaling is investigated and incorporated in the view to enhance classification performance. A CNN model built from scratch is trained and optimized through the Adam optimizer and the best model is evolved when the dropout is set to 30%. The model achieves commendable performance in left and right eye identification and can be used in real-life scenarios. The model has also been fine-tuned to classify left and right eyes for images from other publicly available benchmark datasets and proved to accomplish outstanding performance.

Further, this work can be extended to identify retinal anatomical structures based on whether it is a left or right eye. Computational learning methods can be derived for other dimensions of retinal image analysis such as retinal disease detection, segmentation of retinal anatomical structures, and so on.

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Author's Contribution Statement

K. Kayathri: Conceptualization, implementation of the methodology, interpretation of results, writing - original draft and data collection.
A. Pethalakshmi: Supervision, the framework of the methodology, and critical feedback to shape the manuscript.

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