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Detection And Classification Of Diabetic Retinopathy Using Adaptive Boosting And Artificial Neural Network

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Abstract: The disorders identified with retina of the eye such as: Diabetic Retinopathy (DR), age-related Macular Degeneration (AMD), Glaucoma, etc. can cause visual impairments. The retinal fundus pictures of the patients can be acquired with a computerized fundus camera. It can then be used as machine learning application against the manual technique for the detection and prevention of DR. In this research, the retinal fundus image obtained from Himalaya Eye Hospital Pokhara, MESSIDOR database and EyePACS are used for the detection of DR along with its severity label. In the preprocessing phase, the images are first converted to grayscale images. Histogram equalization technique is performed to adjust image intensity in order to enhance contrast. Median filtering, a non-linear digital filtering technique, is implemented to remove noise present in the image. It too helps to improve the result for further processing. Blood vessels are detected and optic discs are identified and removed. Exudates are segmented for further processing. Finally, selected features are extracted for classification. The classification by Adaptive Boosting (AdaBoost) classifier using selected features achieved precision: 0.642, sensitivity: 0.870, accuracy: 0.620 and F1-score: 0.739. While the Artificial Neural Network achieved an accuracy of 98.43% for the detection of Diabetic retinopathy and 84.21% for the severity classification as stage 0: No-DR, 1: Mild-DR, 2: Moderate-DR, 3: Severe-DR and 4: Proferative-DR.

Keywords: AdaBoost, Artificial Neural Network, Diabetic Retinopathy, Histogram equalization, Median Filtering

I. INTRODUCTION

It is estimated that in low and middle-income countries, 80% of diabetic deaths occur. Diabetes may not directly lead to death but then, it is becoming a leading cause of blindness worldwide. [1] The global prevalence of diabetic retinopathy is 34.6% among the diabetic population. [2] In Nepal, the occurrence of diabetes among people of 20 years and above was 14.6% while among people aged 40 years and above is 19% and 14% prevalence of DR is also identified by some hospital-based studies. [3, 4, 5] An analysis conducted worldwide from 1980 to 2008 involving 35 studies estimated that the global prevalence of any diabetic retinopathy and proliferative DR among patients is 35.4% and 7.5%, respectively. [6] Early detection and diagnosis have been identified as one of the way to achieve a reduction in the percentage of visual impairment caused by diabetes. Diabetic Retinopathy damages the small blood vessels of the retina and may lead to vision impairment. The disease can be classified into four stages. They are no DR, Mild DR, Moderate DR, severe DR and Proliferative DR. Eyes are healthy during the stage of no DR. During the Mild DR stage, small balloon-like swelling occur in the retina's tiny blood vessels. These are called microaneurysms and may leak fluid into the retina. As the disease progresses, during Moderate DR, blood vessels that nourish the retina may swell and distort eventually and may also lose their ability to transport blood. During Severe DR, many blood vessels are blocked, depriving blood supply into the retina. Proliferative DR is the last stage of Diabetic Retinopathy. Growth factors secreted by the retina trigger production of new blood vessels, which grow in the surface of the retina and into the transparent gel that eventually fills the eye. They are more likely to leak and bleed. Eventually, retinal detachment can lead to permanent vision loss. [7, 8, 9] This is a research work about the implementation details, underlying principles and results of Diabetic Retinopathy Detection and Classification using AdaBoost as supervised machine learning model along with the ANN approach. Initially, retinal fundus images from standard dataset were taken. Each retinal fundus images were preprocessed. In preprocessing stage, grayscale conversion, median filtering and histogram equalization were implemented. Blood vessels detection and removal, followed by optic disc identification and removal were also carried out. Exudates were identified and were segmented. The area of exudates were calculated. Feature extraction procedure were carried out. Contrast, energy, homogeneity, angular moment, dissimilarly, and correlation were achieved. Standard datasets and local datasets were prepared that contained all these features along with risk of macular edema, area of exudate and class label. These sets were used for comparison. The simulations were also carried out with the variation of the number of training and testing set. Above stated conditions were applied for both AdaBoost classifiers along with the Artificial Neural Network. The results were also tested and simulated parameters were observed and analyzed to test the accuracy, precision, sensitivity and F1-Score (Fig. 1).

II. RELATED WORKS

The retinal microvasculature can be easily photographed for digital image analysis and is the only part of human circulation that can be directly visualized non-invasively in vivo. A designed matched filter was applied on the image to detect the blood vessels. By thresholding, binarised images were obtained. Perception based binarisation was implemented to overcome the discontinuous lines in detection. A matrix was generated to store the number of matched filters. Blood vessels were extracted pixel by pixel. Random Forest classifier was used for classification. The proposed method of classification based on area and perimeter of blood vessels and hemorrhages produced significant results [10]. ImageMagick software was used to extract suitable feature. Gray level co-occurrence matrices and statistical moments were used for this purpose. Texture features contained energy, dissimilarity, angular moment, correlation and contrast. Three different angles were chosen and two distances were taken. Mean, variance, kurtosis, skewness are among the statistical moments. 40 different features were extracted using feature extraction procedure. Altogether, 1200 datasets were taken. 5 different types of classifiers were used. The dataset was separated into training and test set where 5 fold average CV accuracy was calculated on training set [11]. Giraddi et al carried research on detection of the exudates in the color variability and contrast of retinal images. Comparative analysis was made for KNN and SVM classifier for its detection. [12] In another research, Probabilistic Neural Network (PNN) and Support Vector Machine were used to diagnosis retinopathy. The input retinal images were pre-processed using grayscale conversion, matched filter , AHE and fuzzy C-means segmentation. It achieved an accuracy of 89.6 % and SVM 97.608 %. [13] An automatic segmentation of the blood vessels in fundus images was carried by Melinsack et al. It containend deep max-pooling convolutional neural networks in order to segment the blood vessels. [14] New deep learning based computer-aided system for microaneurysm detection was purposed. Comparing to other deep neural network, it required less preprocessing and more deep layers for training and testing the dataset of fundus images. [15] Overall other methods [16, 17, 18] centered around the key increasing of training and validation accuracy of retinopathy detection.

III. PROPOSED RESEARCH FOCUS

Following, (Fig. 1), are the aspects in which the research focused on:

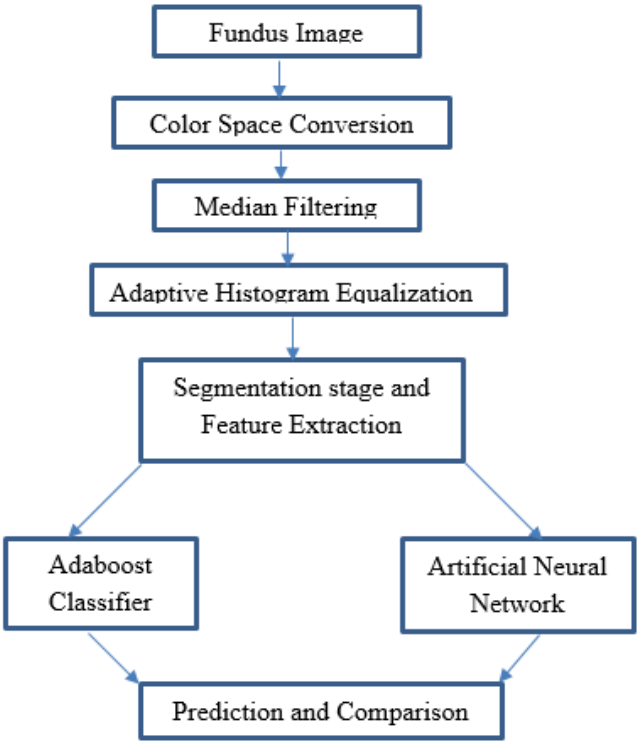

Fig. 1. *Methodology of analyzing the performance of the classifiers*

A. Image preprocessing

To correct the problems of uneven illumination, insufficient contrast between exudates and image background pixels pre-processing is to be carried out. Presence of noise in the input fundus image may mislead the accuracy. Also, for the color-space-conversion and image size standardization, pre-processing is essential. Gray scale conversion of color fundus images and contrast limited adaptive histogram equalization of those gray scale images are used for preprocessing of fundus images. The steps for color space conversion are:

1. Read the image
2. Obtain the dimensions (width and height)
3. For i=0 to width
4. For j=0 to height
5. Obtain pixels for RGB
6. Grey = (R*0.299) + (G*0.587) + (B*0.114)
7. Pixels (i, j) = (grey, grey, grey)
8. Return image

Retinal images (Fig.2: left) obtained from the digital fundoscope were preprocessed so that the images would be suitable enough for further processing. Initially, green channel images (Fig.2: right) were obtained. Figure below shows the sample of unprocessed image and the converted images respectively.

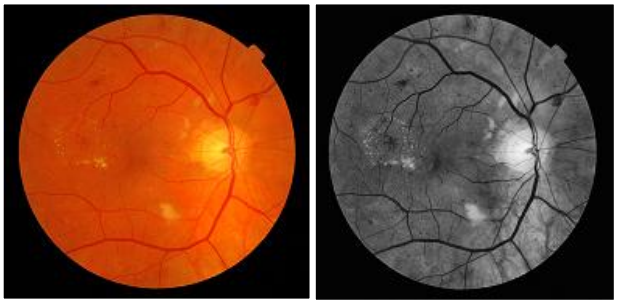

Fig. 2. *Unprocessed retinal fundus image (left) and green channel image (right)*

Similarly, the blue channel (Fig.3: left) and red channel images (Fig.3: right) of unprocessed image are shown in figure below:

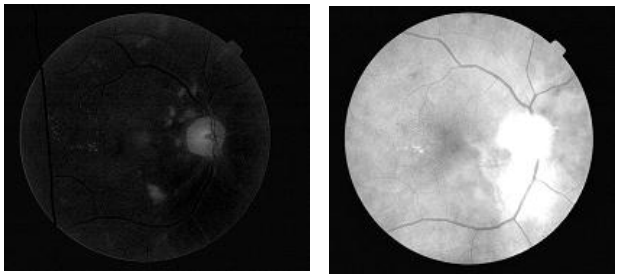

Fig. 3. *Sample output of blue channel image (left) and red channel image (right)*

B. Median filtering

Median filtering operation is applied for the replacement of a pixel by the median of all pixels in the neighborhood of small sliding-window. Median filtering is used to remove noise acquired during image acquisition phase. The main purpose of the adaptive median filter is to remove the salt and pepper noises, smoothing the image, and hence reducing distortions appeared due to the thinness and thickness of image boundaries.

C. Image Segmentation

Simple thresholding is a simple and highly intuitive method of segmenting image based on the pixel intensity value. This method is based on the assumption that the intensity value of the image can be group into two non-overlapping groups. Based on the perceived histogram of the image, the two groups are object and background. Suppose the intensity of an object is denoted by function f(x, y). In this case, it can be seen that the image intensity can be group into two non-overlapping classes based on the obtained value of threshold (T) in the histogram. This help in distinguishing any pixel with value below this threshold, i.e. $f(x, y) < T$ into a class called Background Information and any pixel with intensity value greater than that of T viz. $f(x, y) > T$ into another class called Object. In the segmented binary image, background pixels have value of zero while object pixels have value 1. That is:

$$g(x, y) = 1 \text{ if } f(x, y) > T \text{ and}$$
$$g(x, y) = 0 \text{ if } f(x, y) < T \quad (1)$$

For constant threshold T, this thresholding is called Global Thresholding.

D. Optic Disc Detection

The visible part of the optic nerve head within the retina is the optic disc. It is generally brighter than the neighboring area with an elliptical contour. Variation in pigmentation within normal eyes causes differences in appearance of the disc. Localization of the optic disc is essential in order to differentiate the disc from exudates, cotton wool spots etc. Following are the steps implemented for optic disc detection and removal:

1. Read the image
2. Set the threshold and window size
3. Take value of r to be 10 initially
4. The general representation of circle is $x+r\cos\theta$; $y+r\sin\theta$; where, θ varies between 0 and 360 degree. Take step to be unity
5. Obtain the circumference of the circle.
6. Take first point as center and choose pixel above and below it
7. Compute pixel intensity difference and compare with threshold value
8. Check if it is greater than threshold or not. If yes, make center point dark
9. Shift the center point upward and repeat step 6 to 8 until the difference is greater than threshold value
10. Increment value of 'r' and perform the above steps for all points in the circumference
11. Find mean radius and mean center
12. Draw circle of best fit with mean center and mean radius

E. Vessel Detection and Removal

To detect the retinopathy localization of the optic disc plays a vital role. In certain positions of the retina, the vessels density in the optic disc area is higher. Therefore, by tracking the vessels and identifying the location with the highest density of vessels (Fig. 4), localization of the optic disc is possible. Vessels have similar concentration level that of exudate. Dilation operator on intensity image helps to eliminate high contrast vessels. By laying structuring element (SE) on the image and sliding over the image the operation is performed. SE that describes flat disc shaped structure is used for removing the vessels from optic disc region. If SE stats from brighter pixel, then there is no change and it moves to next pixel. If started from darker pixel, the pixels are made black from images covered by SE.

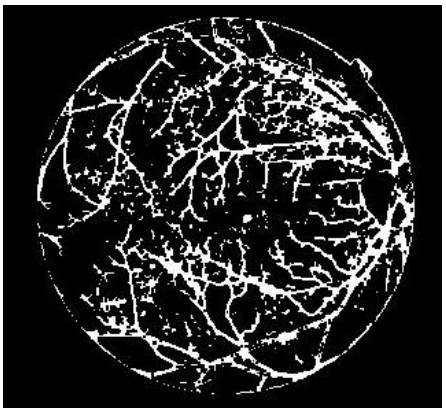

Fig. 4. *Blood vessels identification for its removal*

The edge detected image gets dialated. The erosion operator is used on this dialated image to completely remove the

blood vessel from the retinal image. In image processing, dilation and erosion are used most often in various different combinations. An image may be subjected to series of dilations and/or erosions through the use of same or different SE. The combination of this two principles leads to morphological image opening and morphological image closing. Morphological opening can be described as an erosion operation that is followed by dilation operation.

F. Exudate Detection

After removing the optic disc and blood vessel from an image, exudates is detected (Fig. 5) by closing operator. Image closing operator will be performed on the eroded image as dilation is followed by erosion. It can distinguish the exudates portion from non-exudate pixels. Following are the steps performed for vessel detection, removal and exudate detection:

1. Read image
2. Set size of structuring element.
3. Lay structuring element (SE) on the image
4. Slide the SE over the image
5. Start from darker pixel and apply disc shaped SE on the image
6. Perform edge detection and apply dilation operator
7. Perform erosion to minimize objects by etching boundaries without affecting other segments in order to remove blood vessels from retinal image.
8. After removal of optic disc and blood vessels perform closing operation where dilation is followed by erosion.
9. Image A closing by structuring element B is defined by: $A.B = (A \oplus B) \Theta B$ (2)

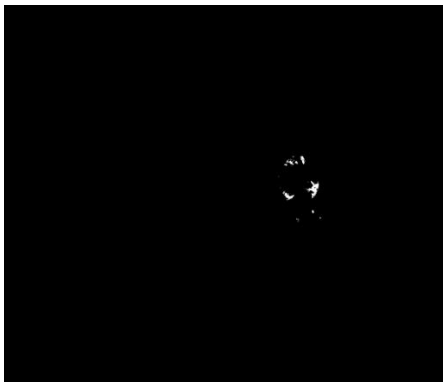

Fig. 5. *Segmented exudate after removal of blood vessel and optic disc*

G. Feature Extraction

After segmenting exudate regions, AdaBoost Classifier and ANN are fed with the segmented image separately. Classifier are used to evaluate training data to find the best method to classify images. The input features required for the AdaBoost are obtained by using Gray Level Co-occurrence Matrix (GLCM). Information about the positions of pixels having gray level values is contained in it. It makes use of distance vector as well. The GLCM is represented as G(i, j) to calculate all pair of pixels separated by distance vector having gray levels i, j. Contrast, energy, homogeneity, correlation, dissimilarity, ASM (angular second moment) are the features obtained. The formula for extracted features are:

$$\text{Contrast}=\sum_{i}^{levels-1}\sum_{j}^{levels-1}(i,j)^2 G(i,j)$$
$$\text{Energy}=\sum_{i}^{levels-1}\sum_{j}^{levels-1}\left(G(i,j)\right)^2$$
$$\text{Homogeneity}=\sum_{i,j}^{levels.1}\left(G(i,j)\right)^1/[1+|i-j|]$$
$$\text{ASM}=\sum_{i,j}^{levels-1} G(i,j)^2$$
$$\text{Dissimilarity}=\sum_{i,j}^{levels-1} G(i,j)(i-j) \quad (3)$$

H. Classification

Classifiers based on extracted features are trained and are used to classify the images as eyes with No DR and Severity labels of DR. Supervised machine learning algorithm (Adaboost) is implemented along with the Artificial Neural Network. In deep learning, the architecture of convolutional neural network layers [19] is particularly well-adapted for the classification of images. For multi-class classification, this architecture is found to be robust and sensitive to the features present in the images.

1) AdaBoost Classifier

AdaBoost learning procedure consists of 'M' iterations. In each iteration, a weak classifier is learned using appropriate machine learning algorithm. Training samples that are classified correctly get a smaller weight, whereas, the weight of all other training sample that are not classified correctly remain the same. The effect is that in the training samples that have been classified correctly have less influence than the incorrectly classified training sample. The model in the next iteration is more adapted to previously misclassified samples. The final classifier is a linear combination of all 'M' weak classifier. Weak classifier with small error rate obtain a large weight than weak classifiers with a high error rate. A set of 3157 training samples is taken. Altogether, there are two classes (0 and 1). Nine different attributes are taken. X is training sample. Vector C is the class level. 'W' provides initial weight of all training samples.

$$W = \frac{1}{\text{No.of Samples}} \quad (4)$$

The number of weak classifier is taken to be 5 (M=5).

Threshold feature is determined that best separates the negative (class label 0) from positive (class label 1) training samples. Logistic Regression is applied as learning algorithm in our case. Once the best features and corresponding threshold of current iteration is determined, the weighted error 'J' is applied on the training data to compute the variables β and α.

$$\beta = \frac{J}{1-J} \quad (5)$$

This beta is applied to adapt the weights of the training samples for next iteration. Whereas α is the coefficient that determines how robust the currently learned weak classifier pays to the final classifier. Array best classifier holds the parameter feature index, threshold and alpha. These parameters uniquely define the final strong classifier. The strong classifier is finally applied to different input vectors defined in the array new data. The decision criteria is that if the linear combination of strong classifier is larger than half of the sum of all 5-alpha values then the predicted class label is '0' otherwise it is '1'. Results are summarized as in the TABLE I:

TABLE I: *RESULTS OF ADAPTIVE BOOSTING ALGORITHM WITH VARYING DATASETS*

Training Data Source	Precision	Sensitivity	Accuracy	F1 Score
Local Dataset (Himalaya Eye Hospital, Nepal)	0.653	1	0.653	0.790
Standard Dataset (MESSIDOR and EyePACS)	0.642	0.8709	0.62	0.739

2) Artificial Neural Network (Deep Learning)

Initially, the preprocessed images are stored in the form of numpy files. The images and labels (probability of Diabetic Retinopathy along with its severity labels) are converted to array information so that we can pass through our network for training purpose. Multiple layered convolutional neural networks are designed and trained with different hyper-parameter values, changing behavior of the training curves are analyzed and the one with best evaluation metrics is finalized. Moreover, different optimization algorithms are implemented to further improve the performance of model. The comparison of parameters and output result of ANN architectures are shown as in TABLE II as below:

TABLE II: *COMPARISON OF ARTIFICIAL NEURAL NETWORK ARCHITECTURES WITH VARYING PARAMETERS*

	Learning Rate	Activation Function	Optimization Algorithm	Batch Size	Input Image Size	Ratio (Training Set : Testing Set)	Dropout	Accuracy	F1 Score	Precision	Recall
ARCHITECTURE I	0.01	ReLU	Stochastic Gradient Descent	32	256*256	75:25	0.6	79.56%	0.53	0.67	0.63
ARCHITECTURE II	0.001	ReLU	Adam's Optimizer	128	256*256	80:20	0.5	84.77%	0.63	0.73	0.77
ARCHITECTURE III	0.003	ReLU + Softmax in output layer	Adam's Optimizer	128	256*256	80:20	0.8	98.43%	0.83	0.87	0.79

Neural Network Architecture (Case I) consisting of four hidden layers resulted the highest accuracy without overfitting. In pooling, we pass convolutional neural network and the window size. Rectified linear function ReLU, (ReLU(x) = max(0, x)), is used as activation function. In this ANN, fully-connected layer is followed by dropout (dropout rate 0.8). Softmax function is used as activation function in the Output layer.

We run regression on Convolutional Network and Adam is used as an optimization algorithm instead of the classical stochastic gradient descent. The learning rate is 0.003 and training and testing split is 80:20. The training and validation curves (Fig. 6 and Fig. 7) are shown for both the cases along with the loss/validation curve in both scenario.

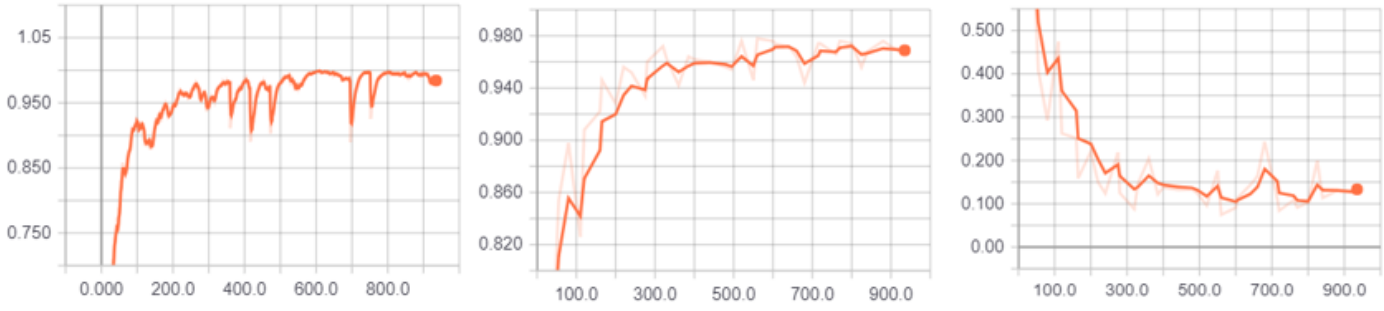

Fig. 6. *CASE I: Diabetic Retinopathy detection (0 and 1). Training curve with accuracy 98.43% (left), Validation curve with validation accuracy 96.89% (middle), loss/validation curve with loss=0.1406(right)*

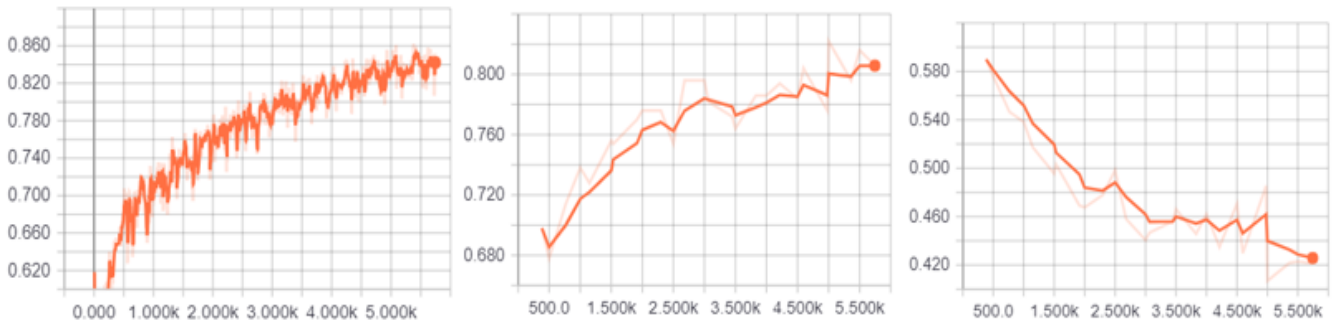

Fig. 7. *CASE II: Diabetic Retinopathy detection with severity label 0, 1, 2, 3 and 4. Training curve with accuracy 84.21% (left), Validation curve with validation accuracy 80.58% (middle), loss/validation curve with loss=0.4214(right)*

IV. RESULT

AdaBoost as an implementation of supervised Machine learning algorithm scored precision: 0.653, sensitivity:1, accuracy: 0.653 and F1-score: 0.790 for the local (Himalaya Eye Hospital, Pokhara, Nepal) and precision: 0.642, sensitivity: 0.8709, accuracy: 0.62 and F1-score: 0.739 for the standard dataset. In addition to this, Artificial neural network achieved impressive results (training accuracy: 98.43% and testing accuracy: 96.89%) for CASE I (Fig. 6) and (training accuracy: 84.21% and testing accuracy: 80.89%) for CASE II (Fig. 7).

V. CONCLUSION

We explored different layered convolutional neural network, trained the eye images with most suitable hyper-parameters, and got the one with best evaluation metrics. Artificial Neural Network performed very impressive in this result compared to the supervised machine learning algorithm: AdaBoost. Local Dataset (Himalaya Eye Hospital, Nepal) resulted in poor output in comparison to Standard Dataset (MESSIDOR and EyePACS) since the quality of local fundus images are not as sophisticated as of standard dataset. Collecting more data samples of fundus images can result in highest possible accuracy. In addition to this, increasing input features can also be used to see its impact on the model performance.

Data availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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