Convolutional Neural Network Modeling for Eye Disease Recognition

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Abstract—The eye is an important sensing organ of the human body, as it reacts to light and allows vision for humans. Many Bangladeshi people become nearsighted when it comes to the awareness of vision loss due to eye disease. Many Bangladeshis people are more concerned about losing their money than getting nearsighted or blind, due to a combination of poverty and illiteracy. With this view, this paper proposes an osteopathic expert system that can deal with an image of the eye and recognize the disease. Here, we have focused on the three most common eye diseases in Bangladesh, namely cataract, chalazion, and squint. We have modeled six convolutional neural networks (CNN's), namely VGG16, VGG19, MobileNet, Xception, InceptionV3, and DenseNet121 to recognize the diseases. We have reached the best configuration of each of these CNN models after adequate investigation. After performing satisfactory experimentation, we have found that the MobileNet model gives the best performance based on accuracy, precision, recall, and F1-score. At last, we have compared our findings with the recently reported relevant works to show their efficacy.

Keywords—eye diseases, osteopathic expert system, CNN, VGG16, performance metrics, accuracy

1 Introduction

Bangladesh is a densely populated country. Most of the people in our country live in rural areas. In rural areas, people rarely have the chance to find out medical-related services. As per the yearly health bulletin of the Health Ministry of Bangladesh [1], there are only 6 doctors and nurses for every 10,000 people in Bangladesh, which is a too small number to ensure health-related services. Most of the people of our country are not conscious of their health and also live in an area where communication way is not so good. Eye diseases are globally considered one of the major contributors to nonfatal disabling conditions. In Bangladesh, 1.5% of adults are blind and 21.6% have a low vision [2]. The main reason for this is that people cannot diagnose their diseases at the right time. Some common eye diseases can sometimes be a big threat if people are not well aware of them. There are many eye diseases that people encounter in daily life. Patients with common eye diseases like cataract, chalazion, squint, etc. are found in almost all areas of Bangladesh. Most people have no clear idea about these diseases, and consequently, the patients suffer a lot. Sometimes wrong diagnosis or treatment results in the loss of the patient's eye forever. An osteopathic expert system is a solution to this problem scenario.

In this work, we have profoundly modeled the convolutional neural network (CNN) model for recognizing eye diseases commonly prevailed in Bangladesh. We have collected four types of images—three common eye diseases as well as a normal eye. After the collection of the images, we also go through a few pre-processing steps so that we can make our dataset large, diversified, and robust. Then we have modeled six state-of-the-art CNN models, such as VGG16, VGG19, MobileNet, Xception, InceptionV3, and DenseNet121. We have tuned the hyper-parameters of these models and come up with the suitable one for each of these models. Finally, we compare the performances of these models in terms of four significant metrics, namely accuracy, precision, recall, and F1-score to find the best model among them.

The rest of the paper has been divided into six sections. In the second section, we describe related works that are close to our topic, whereas the third section describes the research methodology. In section 4, we describe experimental evaluation, and section 5 exhibits a comparative analysis of results. Finally, the conclusion and future work are presented in section 6.

2 Related works

There has been little work done about eye diseases, which provides us with considerable research opportunities. Sarki et al. [3] stated a system for predicting the eye disease of a diabetic patient. They employed a pretrained CNN combined with image processing methods to create an early DED (Diabetic Eye Disease) recognition system. Another great work is done by Zhang et al. [4]. They demonstrate a new system that detects cataracts automatically based on the deep CNN (DCNN) classification. With a dataset made up of 5620 images, they have been able to achieve 93.52% accuracy. Munson et al. [5] also present a smartphone-based application that recognizes leukocoria eye disease in childhood photographs. They applied artificial neural networks for their research work. In the work done by Umesh et al. [6], an expert system that aims to give patients and diagnosis of eye disease has been introduced. For their research work, they applied 4 classification models Naive Bayes, *k*-Nearest Neighbor (*k*-NN), support vector machine (SVM), and Hidden Markov Model. Their experiments on the retinal fundus photographs show that the recommended framework increases the classification accuracy of conventional *k*-NN from 78.57% to 92.85%. Another work is done by Rhatigan et al. [7], which performed on blindness in patients with diabetes who have been screened for eye disease. They used mobile fundus photography. They have collected 5,390 patients' images by the mobile unit over 6 years to get a better result. Another example of this type of work was done by Attebo et al. [8], they are provided a survey in Australia to find out the knowledge and awareness about common eye diseases, they survey three eye diseases cataract, glaucoma, and age-related macular degeneration (AMD). They found that the awareness of cataracts, glaucoma, and AMD is 98%, 93%, and 20% respectively among the people who were aware of the eye disease. The survey was based on the population of people aged 39 and over in the city. Eye disease recognition was done by Grassmann et al. [9], they used a deep learning algorithm for Prediction of Age-Related Eye Diseases Study Severity Scale for Age-Related Macular Degeneration from Color Fundus Photography. They have trained 6 state-of-the-art CNN's separately on 86,770 images as the training data. The algorithm detected 84.2% of all fundus images with definite signs of early or late AMD. Samreen et al. [10] propose a feasible algorithm model that can predict brain tumor possibility by using convolutional neural networks. Hadiyoso et al. proposed a deep learning image-based ECG categorization system. It can detect irregularities in the ECG [11]. Oualla et al. introduced an image-based algorithm for recognizing multiple human faces in haar-like features to represent the invariant characteristics of a face [12]. Shweikeh et al. [13] demonstrate a deep learning algorithm for cancer diagnosis and detection by analyzing the medical images. Yang et al. [14] intend to use a neural network classifier for automatic cataract recognition based on the classification of retinal photographs. An automated eye disease recognition system. An automated eye disease identification method using visually perceptible indications applying digital image processing techniques and machine learning techniques has been proposed by Akram et al. [15]. A truly excellent job was done by Prasad et al. [16]. He suggested a deep neural network prototype that helps us to identify the presence of diabetic retinopathy and glaucoma at its beginning stages. It can alert the patients to advise an ophthalmologist from a screening viewpoint.

3 Research methodology

We have mainly conducted our research for the three most common types of disease as well as one disease-free eye image. Collected images are in different sizes which we resize to a fixed size. Our dataset contains a large amount of data to ensure the performance of the system. Firstly, we split our dataset into two parts, namely train and test datasets. The training dataset contains 80% of the whole dataset whereas the test dataset contains 20% of the data. We have employed six pre-trained CNN models VGG16, VGG19, MobileNet, Xception, InceptionV3, and DenseNet121 on our training dataset. Then what are we going to do that last layer that every particular model has to remove? Because the pre-trained model has thousands of layers. Though we worked on four categories of images. So we added the 4 output layers. This is called the art of algorithm of transfer learning. In all the models, 10^{-3} has been used as the learning rate for both the Adam and RMSprop optimizer. To reduce the error rate, we used Adam and RMSprop optimizer equations, (1) and (2), which update network weights iteratively in the training dataset by replacing the stochastic gradient descent method. Adam and RMSprop optimizer play a key role to minimize the error. To perform our work, all the deep learning models have been trained with GPU support. Then we needed to collect our required images and pre-process them. After that, we applied different deep learning algorithms and analyzed their result. Figure 1 shows the whole methodological structure to carry on this research.

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{\widehat{v_t} + \varepsilon}} \widehat{m_t} \tag{1}$$

$$w := w - \frac{\eta}{\sqrt{v(w,t)}} \nabla Qi(w) \tag{2}$$

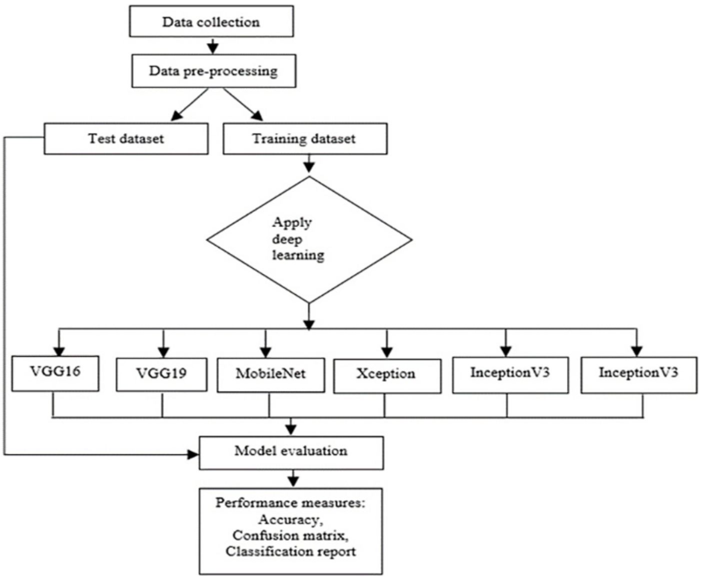
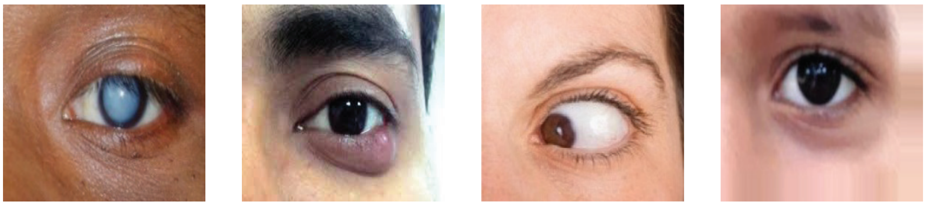


Fig. 1. Steps of our proposed system methodology for eye disease recognition

3.1 Description of disease

There exist many eye diseases among which some are very much prevalent in Bangladesh, especially in rural areas, like cataract, chalazion, squint, and glaucoma [17]. Figure 2 shows a representative image of each of these diseases. These diseases are discussed here.

- **Cataract:** People are affected by this disease when the eye lens becomes cloudy. Even though it starts with minor problems; gradually it becomes the worst problem. During the early stage, prescription glasses can help us but later surgery is mandatory in this regard [18].
- **Chalazion:** A chalazion slow-growing small lump or cyst within the upper or lower eyelid but is more common in the upper eyelid. These are not very painful and last for higher than a few weeks, but they can affect the eye to become more watery and mildly irritated [19].
- **Squint:** The Squint is a condition in which one eye is turned in a direction that is different from the other eye. Normally, six muscles work together for eye movement but patients with this disease have problems with eye movement [20].



(a) Cataract **(b) Chalazion** **(c) Squint** **(d) Normal**

Fig. 2. Three common eye diseases in Bangladesh. (a) Cataract eye. (b) Chalazion eye. (c) Squint eye and, (d) Normal eye (disease-free)

3.2 Dataset preparation and data preprocessing

We have gathered data from some hospitals in different rural areas in Bangladesh. All of these images are captured through smartphones. We have collected some images from the Internet, too.

Fig. 3. Augmented images

Thus, the image dataset in Figure 2 has been prepared with four categories of images consisting of both disease and disease-free eyes. The images collected are in different shapes and sizes. Therefore, we resize the images into the dimension of 224×224. To get accurate results, we augment our images by rotation by 40°, shifting along width and height by 20%, zooming in, zooming out and shearing by 20%, and flipping horizontally by 20% as shown in Figure 3.

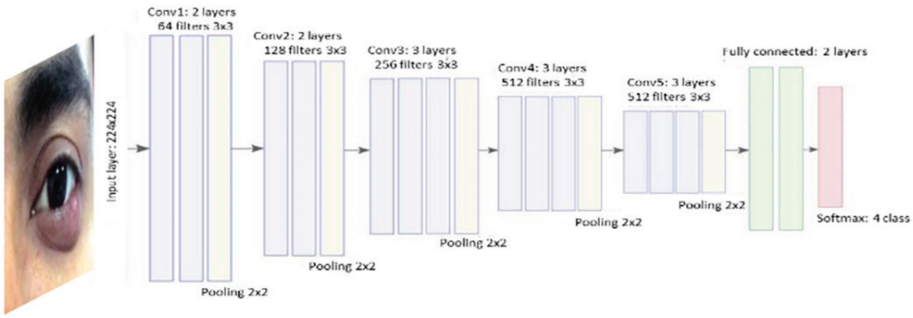
Table 1. Summary of eye disease dataset

Disease Name	Capture Image	After Augmentation	Training Data	Testing Data	Total Training Image	Total Testing Image
Cataract	193	581	465	116	1762	439
Chalazion	205	616	493	123		
Normal	177	531	424	106		
Squint	157	473	379	94		

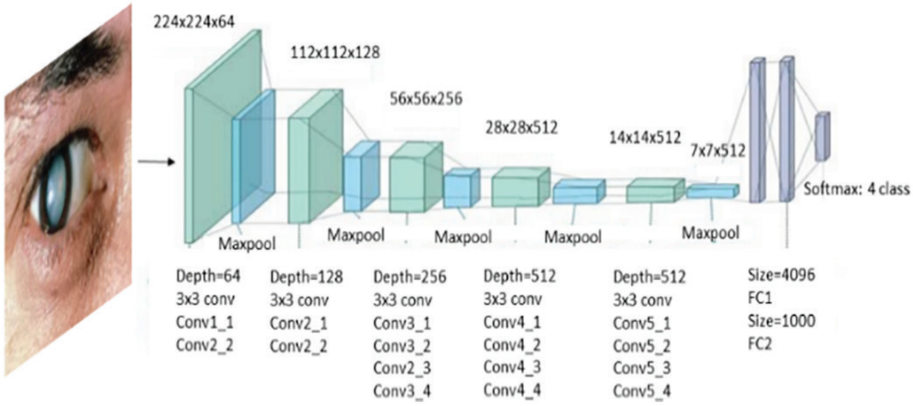
3.3 Description of CNN models

VGG16 proposed by Simonyan and Zisserman [21] is a 16 layer CNN pre-trained CNN model. Since our dataset contains a fixed-size (224×224 pixels) of images with RGB channels, we use (244, 244, 3) as input, where 3 indicates the color image. The softmax function, as equated in (3), is used in the output layer for multiclass classification. VGG19, an alternative VGG model, consists of 19 layers. A pretrained version of VGG19 trained on more than a million images from the ImageNet database can be loaded [22]. Xception is a 71 layer pre-trained CNN model that relies solely on depthwise separable convolutional layers [23]. MobileNet is a 28 layer (treating depthwise and pointwise convolutions as different layers) pretrained CNN model that uses depthwise separable convolutions to render an efficient model for smartphone applications [24]. Inceptionv3 is a 48 layer pre-trained CNN model from the Inception family that makes several improvements including using label smoothing, factorized 7 × 7 convolutions, etc [25]. DenseNet121 is a kind of pre-trained CNN model, which applies dense connections between layers through dense blocks, i.e. all layers are connected (with matching feature-map sizes) to each other directly [26]. The architecture of each of these CNN models is shown in Figure 4.

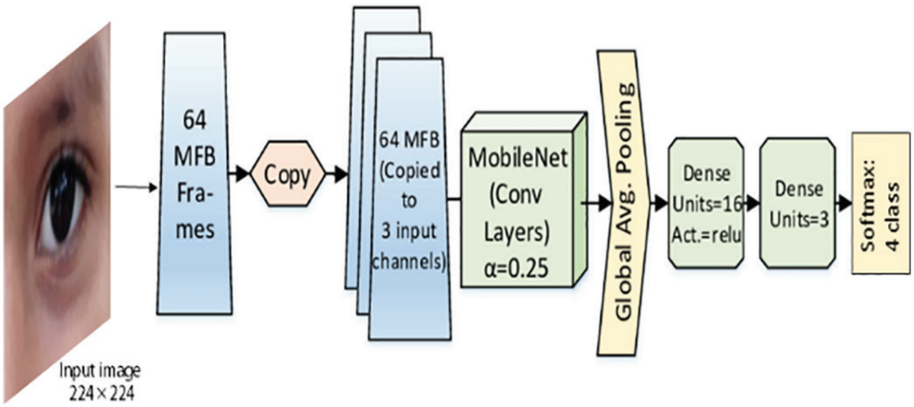
$$\sigma(Z)i = \frac{e^{zi}}{\sum_{j=1}^{K} e^{zj}} \quad \text{for } i = 1, \ldots, k \tag{3}$$



(a) VGG16

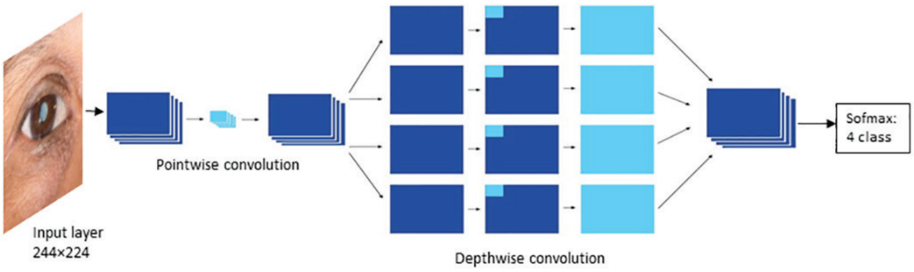


(b) VGG19

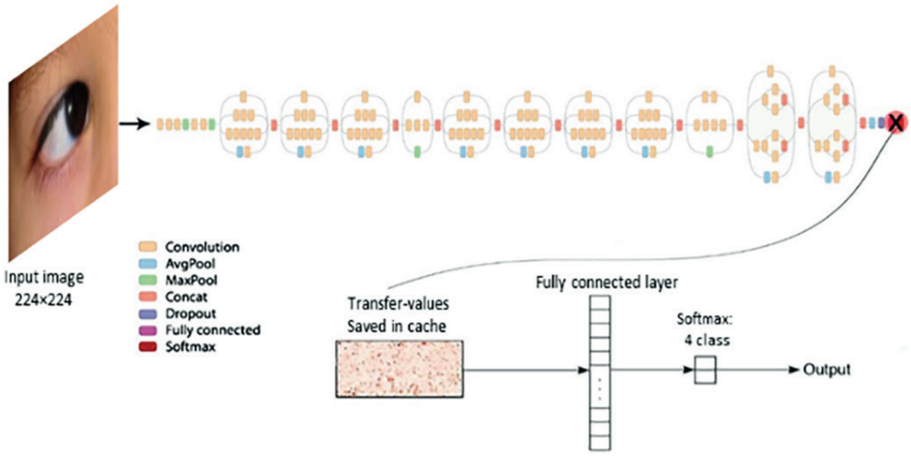


(c) MobileNet

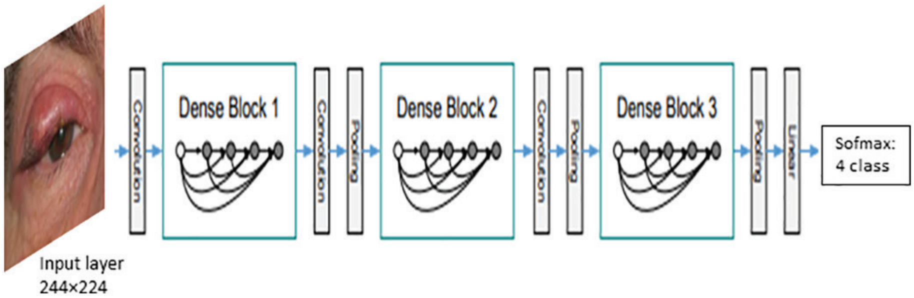
Fig. 4. *(Continued)*



(d) Xception



(e) InceptionV3



(f) DenseNet121

Fig. 4. The architecture of each of the CNN models used. (a) VGG16. (b) VGG19. (c) Xception. (d) MobileNet. (e) InceptionV3. (f) DenseNet121

4 Experimental evaluation

We collect two thousand and twelve disease and disease-free eye color images from four hospitals in Bangladesh with a mobile phone as per Figure 1 and some other images from the internet. Python, Jupyter notebook, TensorFlow, Pyplot, NumPy, and Pandas were used to create the network. Then each image is augmented by rotation and change in lighting, which results in a larger and diversified dataset. Then we resize each image into a fixed-size image of 224×224 pixels. All the data are divided into two subsets called training set and testing set by using the holdout method [27]. We use 80% data as the training part and 20% data as the testing part to evaluate the classifier. To avoid overfitting, regularization is used. Moreover, the values of the corresponding hyper-parameters are set after a lot of experimentation.

Table 2. Multiclass confusion matrix of dimension 4 × 4

Model	Matrix						Model	Matrix					
VGG16	Actual		Predicted				VGG19	Actual		Predicted			
			A	B	C	D				A	B	C	D
		A	93	17	5	1			A	108	4	2	2
		B	1	117	0	5			B	19	100	1	3
		C	0	0	106	0			C	1	1	102	2
		D	1	6	0	87			D	10	6	0	78
Model	Matrix						Model	Matrix					
MobileNet	Actual		Predicted				Xception	Actual		Predicted			
			A	B	C	D				A	B	C	D
		A	106	8	1	1			A	103	6	3	4
		B	1	109	1	2			B	7	110	0	6
		C	0	0	106	0			C	1	0	105	0
		D	0	7	1	86			D	8	6	2	78
Model	Matrix						Model	Matrix					
InceptionV3	Actual		Predicted				DenseNet121	Actual		Predicted			
			A	B	C	D				A	B	C	D
		A	106	9	0	1			A	105	3	4	4
		B	3	119	0	1			B	3	114	0	6
		C	2	5	98	1			C	1	0	105	0
		D	6	10	3	75			D	3	2	1	88

Notes: A = Catarat eye, B = Chalazion eye, C = Normal eye and D = Squint eye.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{4}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{5}$$

$$F_1 Score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \times 100\% \quad (6)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% \quad (7)$$

Those are the confusion matrix, classification report, trained value, accuracy, etc. We figured out the confusion matrix for all models. The confusion matrix is a matrix that uses to measure the performance of the machine learning classification techniques. It is table four with four different combinations of predicted and actual values. After the training dataset, we measure the model performance with the help of the test dataset. In all the models, we found the multiclass confusion matrix result which is shown in Table 2 for measuring the performance of all the models, we have calculated the accuracy, precision, F_1-Score, and recall. To evaluate the performance of our model in terms of the metrics shown in equations (4)–(7). Here TP denotes the true positive and FP denotes the false positive. We use six pre-trained CNN models in our research. So, the metric-wise performance varies from one another model. Table 3 shows the metric-wise result of our six models' accuracy, precision, recall, and F_1-score. The VGG16 model can achieve an accuracy of 95.90% with an average precision of 92.63%, recall of 91.97%, and F_1-score of 91.97%. In VGG19 model can achieve 94.20% accuracy with an average precision of 89.31%, recall of 88.40%, and F_1-score 88.59%. In the model, MobileNet achieved the highest accuracy 97.49% among the six models. The CNN model Xception acquired 95.10% accuracy and average precision 90.20%, recall 90.06%, and F_1-score 90.10%. The rest two models InceptionV3 and DenseNet121 have achieved an accuracy of 95.33% and 96.92% respectively. Then we find out both the training and test accuracy and training and test loss curve for all the six CNN models. Figure 5 displays the training, test accuracy, and training, test loss curve.

Table 3. Metric-wise result of our six model

Model Name	Accuracy	Precision	Recall	F_1-Score
VGG16	95.90%	92.63%	91.97%	91.97%
VGG19	94.20%	89.31%	88.40%	88.59%
MobileNet	97.49%	95.21%	94.83%	94.91%
Xception	95.10%	90.20%	90.06%	90.10%
InceptionV3	95.33%	91.75%	90.10%	90.59%
DenseNet121	96.92%	93.67%	93.97%	93.80%
Mean of all models	96.41%	93.15%	92.97%	92.89%
Standard deviation of all models	0.007212	0.007354	0.014142	0.01294

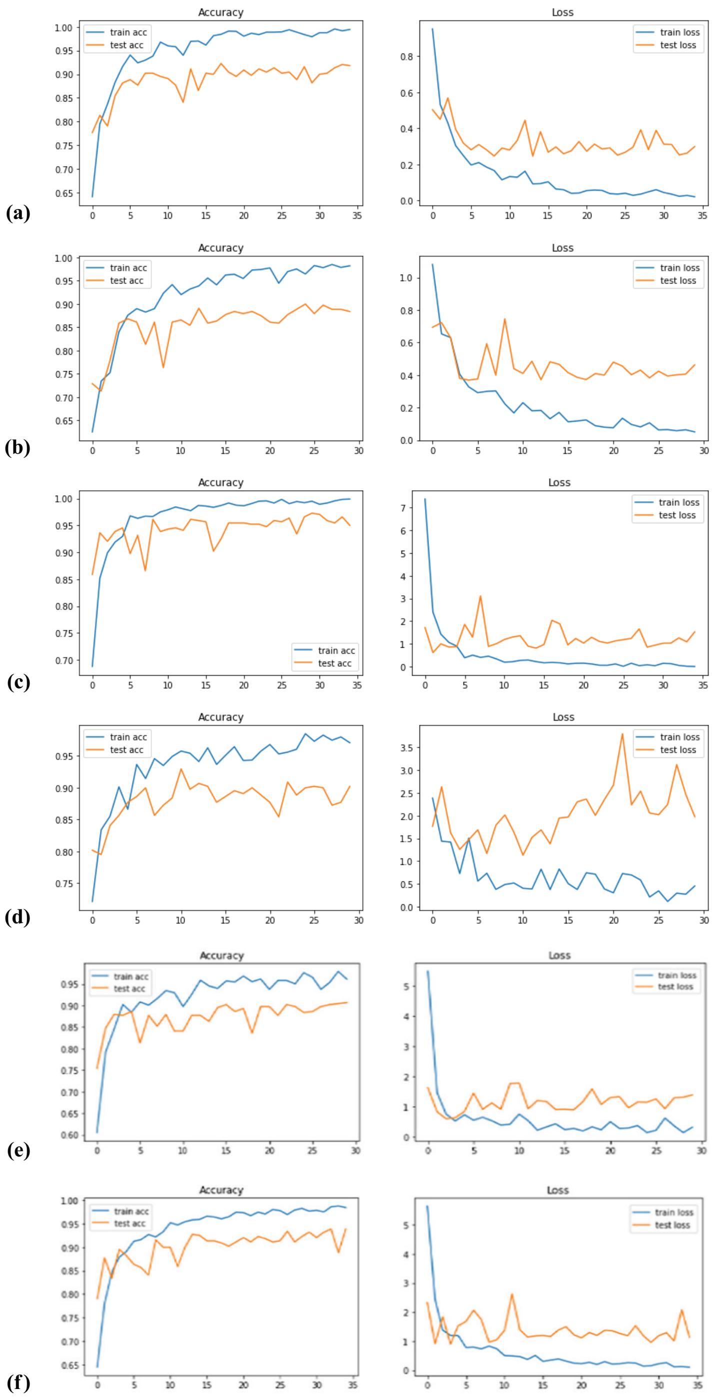


Fig. 5. Training, testing accuracy, and training, testing loss curve. (a) VGG16. (b) VGG19. (c) MobileNet. (d) Xception. (e) InceptiionV3. (f) DenseNet121

Table 4. Different hyper-parameters used in our selected models

Model Name	Input Size	Batch Size	Optimizer	Epoch	Total Parameters
VGG16	224 × 224	16	Adam	35	14,815,044
VGG19	224 × 224	16	Adam	30	20,124,740
MobileNet	224 × 224	32	RMSprop	35	3,429,572
Xception	224 × 224	16	Adam	30	21,262,892
InceptionV3	224 × 224	32	Adam	30	22,007,588
DenseNet121	224 × 224	32	RMSprop	35	7,238,212

Table 4 demonstrates the different hyper-parameters used in our research study. We have come to the suitable values of these hyper-parameters by tuning them vigorously. We have used input image size 224×224 for all six models. For batch size, we have used 16 for VGG16, VGG19, and Xception, and 32 for the rest three models. As an optimizer, we have used Adam (adaptive learning rate optimization algorithm) optimizer method in four models. Where other two models MobileNet and DenseNet121 have used RMSprop (root mean square prop) optimizer. The number of epochs used is 30 and 35 for different models. Batch size is a term that is used in machine learning and indicates the number of training data used in one iteration. We have used batch sizes of 16 and 32 for all six models.

5 Comparative analysis

To evaluate our proposed expert system for eye disease recognition, we need to compare recently published research works on eye disease recognition. We have found that most of the works detect one or two eye diseases, while some of them need few medical tests, which makes the comparison of our work with others unparalleled. Nevertheless, we have attempted to perform a meaningful comparison. Table 5 shows an overview of all methods of different works including our works. A backpropagation neural network classifier was proposed to automatically classify the severity of cataracts [14]. They used 428 images only for training. Through the classifier, the patients' cataracts are classified into normal, mild, medium, or severe ones. The work [15] introduced an automated eye disease recognition system from the visual content of facial images using machine learning techniques. They proposed a system based on an algorithm that automatically crops the eye part from a frontal facial image. They achieved 98.79% accuracy by using SVM and *k*-NN classifiers. Multiple eye disease detection using deep neural network [16] article demonstrates a system that can detect Glaucoma and Diabetic Retinopathy at the early stage. They obtained 80% accuracy by using CNN and the data sample was not mentioned in their paper. Concerning this scenario, we can claim that the results (the maximum accuracy of 97.49%) achieved us is both good and promising.

Table 5. Comparison of our work with other works

Work Done	Problem and Diseases Dealt with	Domain	Sample Data Size	Classifier	Accuracy
This work	Recognition of three common diseases along with normal eye	Deep learning	2201 images	DenseNet121	97.49%
Zhang et al. [1]	Cataract image	Deep learning	5620 images	DCCN	93.52%
Yang et al. [14]	Retinal Image	Classical machine learning	428 images	Back Propagation Neural Network	Not mentioned
Akram et al. [15]	Eye disease image, visual content of facial images	Machine learning (Classical + Deep)	1753 images	DCCN and SVM	98.79%
Prasad et al. [16]	Multiple eye disease image	Deep learning	Not mentioned	CNN	80%

6 Conclusion

Eye diseases problem is a very common and ancient health problem in Bangladesh. Every year many people in our country suffer from their eyes because of a lack of concern about early diagnosis and treatment of their diseases at the right time. Having motivated by this issue, we have tried to build a computer-vision-based osteopathic expert system which is employed with the help of a CNN-based pretrained model. Our system cannot only effectively predict the three types of disease but also the disease-free eye. MobileNet has achieved the highest accuracy of 97.49%, which is a promising result to portray the performance of the system.

Our work provides better results than any other existing system that has already been reported. There remain various future works on automatic eye disease recognition to consider more types of eye diseases with an enormous amount of dataset, which will provide the complete application for almost all of the eye diseases commonly prevalent in Bangladesh.

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