INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Multiclass Classification and Identification of the External Eye Diseases using Deep CNN

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OPEN ACCESS

Received: 03-01-2024
Accepted: 11-02-2024
Published: 14-03-2024

Citation: Rashid F, Abate J, Abdi A (2024) Multiclass Classification and Identification of the External Eye Diseases using Deep CNN. Indian Journal of Science and Technology 17(12): 1107-1116. https://doi.org/10.17485/IJST/v17i12.21

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Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Objective: These eye illnesses can be either internal eye diseases or external eye diseases. The purpose of research is to find the right model for better performance to identify the external eye disease. The model is customised with 16- layers CNN using multiclass classification. **Method:** The Deep CNN techniques are utilized with multiclass classification, and the model is developed using Vgg16 with different dropout rates of 0.25 and 0.50 to improve accuracy and performance. In this work, a deep convolutional neural network model is proposed to classify and identify external eye diseases like conjunctivitis, blepharitis, and cellulitis. Datasets were taken in 80:20 randomly from blepharitis, cellulitis, and Conjunctivitis to test (242) and train (968) the model after pre-processing. **Novelty:** The model is novel and unique using deep CNN, Vgg16, and multiclass classification because it has never been classified and predicted previously for external eye disease. Additionally, Vgg16 with dropout rates of 0.25 and 0.50 was not tested. The model is penetrated into fully connected (FC) layers with different dropout rates. **Findings:** The accuracy of 98.48% and 0.976% for deep CNN and multiclass classification consecutively produced satisfactory results. The efficiency of R^2 is evaluated with multiple classes of data that resulted in a range of 0.425 - 0.775 with k = 10 folds. Vgg16 attains the highest performance of 71.54% with changed dropout rates. The effects of fundus in the ocular, such as retinopathy and AMD, can be examined in the future with segmented data using CNN for better optimization. On account of biological changes in eye and retinal structure, models might be constructed or studied.

Keywords: Multiclass Classification; Identification; Deep CNN; External Eye Disease; Evaluation

1 Introduction

The sight of the human being is a very sensitive and important organ among the other organs of the body. It is spoiling faster than before due to the high use of screens and segregated lifestyle among youngsters. The high perception of 75% - 80% comes from sight, which makes it preferable to protect the eye from damage. It influences doing various research to check eyes disease automatically and more accurately. The diseases are classified as internal and external problems of the eyes. Various AI strategies were applied for internal eye diseases, but none of the studies found those trained for external eye problems using multiclass classification.[1]

Specifically, conjunctivitis, blepharitis, cellulitis, and dry eyes are some of the external eye diseases.[2]. External parts can be readily infected or harmed as the eye has direct exposure to the environment. In addition, a variety of hereditary diseases can impact the external lens of the external eye illnesses are ailments that affect the surface of the eye. It is very difficult to identify such diseases using medical images, as there are very minor differences between the clean image and the infected image.[3] So, very efficient methods are needed to differentiate such images. External eye diseases can be detected using the images captured by the normal camera.

The classification of images is one of the solutions in the model to accurately predict the disease. It helps to categorise and label groups of pixels within an image based on certain rules that are based on spectral characteristics.[1,4] The categories of images for normal and pneumonia[5] using the developed model were identified.

Sometimes machines learn statistical noise during feature learning from the datasets. It improves performance during training but fails on new data points during testing, which is the problem of overfitting. This can be solved using techniques like handling the weight of the network or regularizing the fixed-size model to get an average prediction. Furthermore, the ensemble technique can be used for multiple networks with different architectures. It needs multiple models to be trained and stored, which becomes a challenge as the network grows deeper over time. So, the better solution is to manipulate dropout rates where forward and backward connections with a dropped node are removed temporarily.

Thus, creating a new architecture requires the parameters of the old network. The nodes are dropped by a probability of p. Here, p = 0.25 and p = 0.5, which means that 25% or 50% of total neurons (nodes) in the hidden layers of the network will be dropped in each iteration during training. The greater the drop probability, the sparse model for hidden layers, where 0.5 is the most optimized value of p. Specifically, researchers used other CNN models as shown in Table 6, but Vgg16 is not used by anyone with changed dropout rates of 0.25 and 0.5, which is the major novel proposal in this paper. The standard Equation (1) for forward propagation is:

$$\begin{aligned} Z_i^{(l+1)} &= w_i^{(l+1)} y^1 + b_i^{(l+1)}, \\ y_i^{(l+1)} &= f\left(z_i^{(l=1)}\right) \end{aligned} \tag{1}$$

Where, z = vector of output from layer (l +1), before activation

y = vector of out from layer 1.

w = weight of the layer l.

b = bias of the layer l.

The z is transformed into the output for layer (l+1) with activation.

The forward propagation Equation (2) changed in following manner, if dropout rates applied

$$\begin{aligned} Z_i^{(l+1)} &= w_i^{(l+1)} \tilde{y}^1 + b_i^{(l+1)}, \\ y_i^{(l+1)} &= f\left(z_i^{(l=1)}\right) \end{aligned} \tag{2}$$

y bar ensures that we have thinned output which is given as input to the layer.

External eye diseases like conjunctivitis, blepharitis, cellulitis, and dry eyes[6] are also vital problems for vision. The cornea, iris, macula, pupil, and optic nerve are all part of the human eye's complex structure.[7] Therefore, an efficient technique is needed to detect external eye diseases. An automated model was developed for the classification and identification of external eye diseases.

The benefits of AI were used in this work to classify and identify external eye illnesses.[6] In this work, an automated model is implemented using deep learning (DL), which will classify and identify external eye diseases like conjunctivitis, blepharitis, and cellulitis.

The rise of artificial intelligence (AI) in disease detection and diagnosis in biological sciences during the last few decades. AI has transformed disease detection by automating the time-consuming classification stages formerly performed by professionals.[8] Because of the recent surge in applications using AI-based technologies and physicians' demand to operate with fewer errors, mishaps, and misdiagnoses, the medical industry has been accepting and adopting AI. Many AI and subset DL networks are beneficial in medical image processing for prognosis and diagnosis of various maladies (e.g., breast cancer, lung cancer, and brain tumour), which can be time-consuming and prone to human mistakes if done manually.[9]

These deep learning algorithms are used to handle problems like prediction, segmentation, and classification in medical pictures, effectively bypassing human abilities. The application of AI in the detection and treatment of eye diseases is significant. The method necessitates the proper classification [8,10] identification, and extraction of ocular layers, allowing ophthalmologists to concentrate on the treatment. [11]

Blepharitis is a chronic eye illness in which the eyelids become inflamed. [5,12] It can also produce irritation, burning, red eyes, blurred vision, and sensitivity to light among other symptoms.

Conjunctivitis in pink eyes is an early stage of conjunctivitis effects. The mucous membrane can be affected by various diseases, which can cause discharge, burning, swelling, and redness (sclera). Conjunctivitis is often minor, but it can also be severe. [5,12] Viruses, germs, environmental irritants (allergies), contact lens products, and eye drops are all common causes of conjunctivitis.

In cellulitis, the eyelid is infected and the skin of the orbital septum is anterior, this is known as perceptual cellulitis (periorbital cellulitis). [12] Orbital cellulitis is cellulitis of the orbital tissues posterior to the orbital septum. Reasons for orbital or periorbital cellulitis can be some external source of infection due to a cut etc., infections that start from the teeth or nasal sinuses, or metastatic spread due to other sicknesses.

The images are divided in more than two classes [10,13,14] in the multiclass classification. Each image is assigned to one class without overlap. Various category of images are used with classes using target variables. The unseen sample of x and identifying the label k for which the corresponding classifier reports the highest confidence to build a decision is shown in Equation (3).

$$\begin{aligned} &Y' = argmax\ f_k\,(x) \\ &k \in \{1 \ldots K\} \end{aligned} \tag{3}$$

Values differ between classifiers. It trains K (K-1) /2 classifiers for a K-way multiclass problem. The original training set provides a sample of a pair of classes and learn differently from each class.

Some research gaps are identified, which are as follows:

- Classification is a stronger way of classifying the internal and external diseases of the eyes. Some limited accuracy was observed using normal classification. It directs us to proceed using multiclass classification.
- Maximum of the models focused on only one task for the detection of eye diseases, whereas there was the possibility to make the models perform more than one task. [15,16]
- The work carried out for the detection of external eye diseases [17] suggested improvements in terms of accuracy and speed of training the model. The new model is required to detect external eye diseases effectively.

Therefore, new models are designed for efficiency, which build the classification and identification of external eye diseases with better accuracy and computational speed. The major contributions are:

- Pre-processing the data, then training and testing in the designed CNN model.
- Feature extraction and classification based on client-server architecture by penetrating the layers in Vgg16.
- Validation of the data by generating data matrices, and the performance of fully connected (FC) layers which is learning.
- Evaluation and comparing of the model using balanced data.

Automated models can provide an enhanced outcome for the classification and identification of subclinical fundus characteristics owing to age and find a relationship with demographic factors. [13] Most eye illnesses are diagnosed with AI and deep learning (DL) techniques. Deep CNN diagnoses all the diseases with the same accuracy as human specialists can. So, these techniques are widely adopted for the identification of eye diseases.

The AI-based models have greatly aided ophthalmology in the diagnosis and treatment of retinal disorders. [1,18] The same AI-based algorithms are utilized to recognise eye infections and to assist ophthalmologists in better diagnosing and describing DME, and CNV.

The models have compared to assist the specialists in identifying and grouping eye ailments, and the best picture subtitling model which were compared for the identification. [8,19]

The hierarchical multilevel classification achieved a success rate of 75.5% [5]. DenseNet201 was used, which achieves the highest precision of 0.969. A deep convolutional neural network model was utilized to identify the internal eye disease.

Initially, they built up an enormous scope and an attention-based glaucoma (LAG) information base that incorporates 11,760 fundus pictures classified as either sure glaucoma (4,878) or negative glaucoma (6,882). Then attention-based glaucoma (AG-CNN) is used for glaucoma recognition, which outperforms other models with an accuracy of 96.2%. [20,21] The author suggested that in the future, new models for identification can be implemented, which can be real-time as well.

Furthermore, deep learning (DL) was utilized for the diagnosis process.[16,19] PPA (parapapillary decay) was related to near-sightedness and glaucoma, so the identification of PPA was a substantial indicator for these diseases as well. Glaucoma screening using an optic plate and optic cup division technique based on super-pixel characterization has been studied as an algorithm for detecting retinal arteriovenous (AV) scratching.[21,22]

Overall, they[18] used Vgg19 deep learning with classification produced an accuracy 99.17% for the model. In the case of[16] achieved accuracy of 97% and 81% of predictive and multiclass classification with Shapely Addictive Explanation (SHAP) for diabetic retinopathy (DR), but they used small datasets of 614 only for training and validation. DR images of 1200 men and women were used[16] for a predictive model with ResNet101 and achieved a result of 96.92%. Researchers used transfer deep learning with the Vgg19 model. The accuracy of the model for normal versus counteract was 94.03%.

The evaluation issues become weak if the researcher does not make any cross-validation and error tests, there are probability to receive the biased result.[23] Additionally, none of the mentioned researchers checked the model for MSPE, and 90% did not use multiclass classification, while the multiclass model consists of one node for each class to present better findings. Hence, it offenses to test including local datasets, different techniques, modified tool with dropout rates for the better identification accuracy.

2 Methodology

The proposed work is divided into 5 phases, which are cleaning of data, pre-processing of data, training and testing, cross-validation, classification, identification, evaluation, and model comparison of the diseases. Illustration and flow are shown in Figure 1. Vgg16 was utilized for the image multiclass classification and identification model of the diseases.

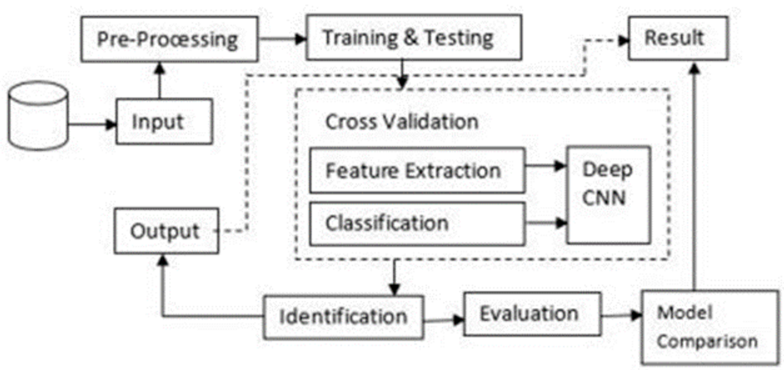

Fig 1. Workflow Model

2.1 Datasets and Analysis

The datasets used in this work were taken from Belyhun,[12] a total of 210, and colour images of infected oculars from www.kaggle.com.[24] There are approximately 1000 fundus eyes images. 168 (80%) out of 210 (22) and 800 (80%) images from Kaggle.com are for training purposes, and the rest (20%) are for testing purposes.

The pre-processing of the data is one of the important steps to apply in the machine model to achieve accuracy. The data were cleaned, normalized, standardized, and transformed in the range of 0-1, to train and test CNN using Python. The height and width of the images were adjusted with a resizing of (224 x 224) because of the standard size accepted by the learning models. The classes of images were: blepharitis (375), cellulitis (248), and conjunctivitis (345). The randomly selected datasets were taken for testing and training purposes. As the function imports the data from each class, the datasets get accessed through the images in each class.

The detailed distribution of datasets is displayed in Table 2. Cross-validation techniques were used to evaluate the model's performance, assuming a CV = 10. Python 3.9.0 was used for experiments and analysis.

2.2 Deep CNN

A convolutional neural network (CNN) is used to detect handwritten numbers in the beginning. The architecture of CNN can be enhanced by adding some essential layers, such as pooling layers (pool), fully connected layers (FC), and convolutional layers (Conv). It would be very effective when dealing with high volumes of data like medical image processing, pattern recognition, image enhancement, and multiclass classification.[10,13,17] The CNN performance of features and patterns of data can be obtained with high accuracy using large datasets.[25] However, smaller datasets can also be trained in CNN with curated data for the target domain for reasonable performance. Many architectures of CNN are developed with various parameters and updates, like VGGNet, AlexNet, GoogleNet, ResNet, and LeNet. Each of the architectures has different strengths and properties to classify the images.[1,5,21,23]

The fundus pictures were pre-prepared by a versatile histogram equalizer and utilized for feature extraction and characterization in two stages: one was based on the location used for external problem recognition, and the other was known as the classification utilized for the arrangement of influenced problems in the pictures into multi-classifications.

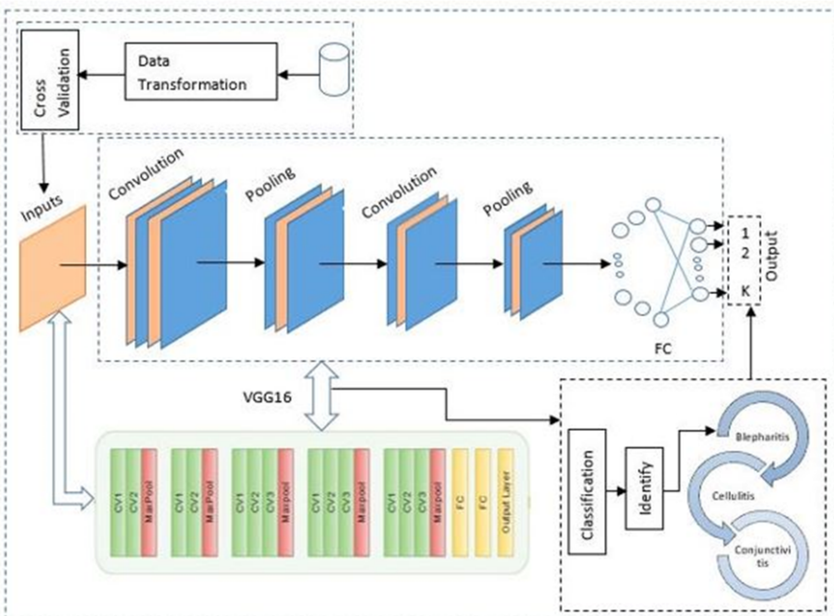

Fig 2. Proposed Architecture CNN

2.3 VGG-16 Architecture

VGG-16 architecture is utilized in this work to detect exterior eye disorders such as conjunctivitis, blepharitis, and cellulitis. It consists of an input layer, a group of convolution layers (CV), and max pool layers. The feature size is maintained by the padding on each CV kernel. Fractional inscriptions are used in the deep CNN model for the prediction. The model is straightforward to set up and use in the analysis process. Figure 2 depicts the proposed architectural structure.

This model is made up of 5 blocks of CV layers, with fully connected layers (FC layers) added at the end. The model consists of 13 CV levels and two FC layers. The model accepts images with a resolution of 224 x 224 pixels. Each layer contains both trainable and non-trainable parameters. These images then pass to the CV layers, which has a filter of 3x3 with stride 1. In each block, at the end, the Max pool layer is there. The window of these layers is non-overlapping, and the window of the 2 x 2 max pool window is used with stride 2. The channel size increases by a factor of 2.

Changes in the parameters occur when the output is sent to the next layer. Batch normalization is employed to solve this problem. This normalization normalizes each layer's input and, to some extent, reduces the error rate and overfitting. Batch normalization enhances the model's performance. To resolve the issue of overfitting, different dropout rates are used. The model has a checkpoint and an early stopping feature. Checkpoints keep track of the stated parameters, and the validation accuracy is kept track, and saved when it is at its highest.

In Table 1, the layer description of the VGG-16 is displayed. The normalization function is also applied to the model so that the error rate can be reduced. Different dropout rates are used to overcome the problem of overfitting.[13]

Table 1. CNN Layers Description

Layers	Output Shape	Parameters	Layers	Output Shape	Parameters
Input layer	224x224,3	0	Maxpool-3	28x28,256	0
Convolutional-1	224x224,64	1792	Convolutional-1	28X28,512	1180160
Convolutional-2	224x224,64	36928	Convolutional-2	28X28,512	2359808
Maxpool-1	112x112,64	0	Convolutional-3	28X28,512	2359808
Convolutional-1	112x112,128	73856	Maxpool-4	14X14,512	0
Convolutional-2	112x112,128	147584	Convolutional-1	14X14,512	2359808
Maxpool-2	56x56,128	0	Convolutional-2	14X14,512	2359808
Convolutional-1	56x56,256	295168	Convolutional-3	14X14,512	2359808
Convolutional-2	56x56,256	590080	Maxpool-5	7X7,512	0
Convolutional-3	56x56,256	590080	Flatten	25088	0
Not Used	Not Used	Not Used	Dense	256	6422784
Not Used	Not Used	Not Used	Dropout	256	0
Not Used	Not Used	Not Used	Dense-1	3	771

3 Results and Discussion

The experiment was carried out on i7, and Python 3.2.9 was used for training, testing, and analysis purposes. The images of external eye defects (blepharitis, cellulitis, and conjunctivitis) were selected randomly. The detailed distribution is shown in Table 2. A total of 3368 images were used for training purposes and 842 images for testing. Thus, 4210 images were used for analysis and multi-class classification.

Table 2. Training and Testing Datasets

Classes	Train		Test		Total
Blepharitis	800 + 168 = 968	375	200 + 42 = 242	94	469
Cellulitis		248		66	314
Conjunctivitis		345		82	427
TOTAL		968		242	1210

3.1 Proposed Vgg16 Model Output

The model is run for 25 epochs, and early stopping is used to save the model with the highest validation accuracy, allowing it to run for up to 10 epochs. The model is executed for two different dropout rates of 0.25 and 0.50, respectively. The model is evaluated using four matrices: loss, accuracy, validation loss, and validation accuracy.

Because different dropout rates are used, the results are reported in Table 3. Validation accuracy is 70 percent with a dropout rate of 0.25, but it is 71.54 percent with a dropout rate of 0.50. So, the model achieves higher accuracy with a 0.50 dropout rate.

The proposed model is executed at two dropout rates for validation purposes. The model got two different validation accuracies for these dropout rates, as shown in Figure 3. The validation loss is rapidly reduced, whereas the validation accuracy is initially reduced and then gradually increased.

Table 3. The output of the proposed Vgg-16 model with a 0.5 drop-out rate

Epoch	Loss	Accuracy	Validation Loss	Validation Accuracy
1	1.1683	0.4971	0.8687	0.6154
2	1.1189	0.4688	1.0179	0.5308
3	1.0162	0.5109	1.0986	0.4846
4	0.9526	0.5457	0.9348	0.5923
5	**0.8977**	**0.5987**	**0.7136**	**0.7154**
6	0.9842	0.5478	0.8378	0.6231
7	0.8393	0.6490	0.2308	1.5364
8	0.9628	0.5701	0.9669	0.5385
9	0.9041	0.5861	0.9860	0.4923
10	0.8387	0.6422	0.8807	0.6000

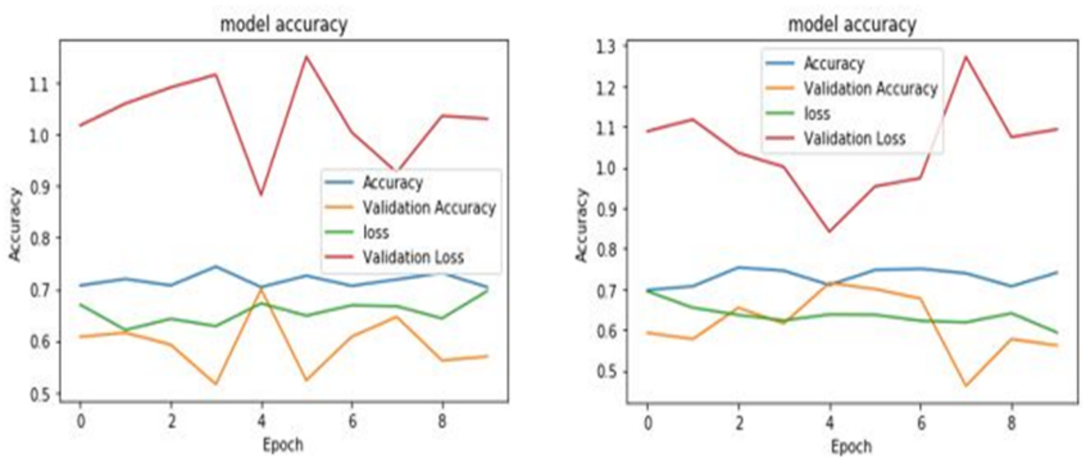

Fig 3. Model accuracy proposed for the Vgg16 model (a) drop-out 0.25 (b) drop-out 0.50

3.2 Evaluation metrics for each class

Evaluating the model with proper data is important to find the accuracy needed to determine whether an image has the disease or not. The proposed model of deep CNN and multiclass classification were tested for the performance of identification using precision, recall, and the F1-score for individual classes shown in Table 4. Overall accuracy for deep CNN is 98.48%, and multiclass classification represents 0.976%, which satisfies the model. The error rate of misclassification that lies between 0 and 1 is 0.032. The second highest priority was given to finding the F1-score for the model and evaluating it on the test set. Vgg16 is used to determine whether the image class has an external category of disease. However, after implementing the model, a satisfactory result is observed with the least misclassification error.

3.3 Cross-validation R2 metric for the model

Cross-validation (CV) is a resampling procedure used to evaluate machine learning models in limited datasets at some data point. The model-building set, is a training set and validation (prediction or identification is used to evaluate the predictive ability. There are chances of losing some important data points for the training purpose, which increases the probability of losing some patterns. It may lead to the issue of overfitting or underfitting the model. To avoid the issue, the k-fold technique of random sampling guarantees the training and validation of datasets to maximize accuracy.

The percentage of variance in the dependent variable (output) is described by the independent variables (input). R^2 is also known as the coefficient of determination used to evaluate the performance of the model that was used to compare the same model for different classes of datasets. The cross-validated R^2 is calculated for each iterative validation, and the average value is taken after the iterations. Like in Python:

scores = cross_val_score(LinearRegression(), Xr, yr, cv=10, scoring = “r2”)

Table 4. Evaluation Performance of Proposed Model

Model	Class	Precision (%)	Recall (%)	F1-Score	Accuracy
Deep CNN (Proposed)	Blepharitis	98.3	97.7	98	98.48
	Cellulitis	97.9	98.8	98.35	
	Conjunctivitis	99.3	99.5	98.95	
Multi-Class Classification	Blepharitis	0.977	0.965	0.971	0.976
	Cellulitis	0.893	0.914	0.903	
	Conjunctivitis	0.982	0.987	0.984	
Misclassification (Error) Rate	Blepharitis	0.012	0.001	0.0184	—
	Cellulitis	0.001	0.002	0.0133	—
	Conjunctivitis	0.032	0.007	0.0114	—

The value close to 1 (also the value of p) implies a better fit in the model. It is important to check whether the proposed model fits with the independent data for various characteristics to predict the response variable. We calculate the prediction error and summarize the predictive ability of the model by the mean square prediction error (MSPE) shown in Equation (4), then scale it to provide a cross-validation R^2 for multiple folds by limiting k = 10 and cyclic classes shown in Table 5. R^2 may mislead the complex model when there is a high degree of multicollinearity among the independent variables. The MSPE was measured to ignore the overconfidence of R^2 and assure the accuracy of the dataset.

$$MSPE = E\left[\sum_{i=1}^{n} \left(g(x_i) - \widehat{g}\ (x_i) square\right)\right] \tag{4}$$

Table 5. R^2 Prediction evaluation

Iteration Test	Class	R^2
Fold_1	class_1	0.68377
Fold_2	class_2	0.71725
Fold_3	class_3	0.69894
Fold_4	class_1	0.57881
Fold_5	class_2	0.77565
…	…	…
Fold_10	class_n	0.42542

K-fold cross-validation was tested by assuming k=10 in multiple iterations by distributing the datasets in 10 random classes. It shows the best result of R^2 is 0.775, closer to 1in the fifth iteration. The results of cross-validation were satisfactory in the context of the data class.

In Table 6, the proposed work is compared with some previous works. The proposed model is different from all these works in that it detects external eye diseases, whereas all the other works shown in the table detect internal eye diseases.

Table 6. Comparative Analysis of the model with similar previous works

Author	Disease Type	Method used	Accuracy
(1) Rafay A. et al. (2023)	Internal Eye Disease	Efficient Net B3	94.30%
(3) Liu R. et al. (2022)	Diabetic Retinopathy, macular Edema	Deep Learning	91.30%, 96. 92%
(16) Shakeri E et al. (2023)	Diabetics, Internal Eye Disease	CNN, SHAP	82.5%.
(20) Aamir M. et al. (2020)	Internal Eye Disease	ML-DCNN	99.39%
(18) Choudhary A. et al. (2023)	Internal Eye Disease, neovascularization	CNN, Vgg19	97.17%
(25) Richa Gupta et al. (2021)	Internal Eye Disease	Deep Learning	99.44%.
Proposed model	External Eye Disease	Deep CNN, Vgg16	98.48%

Methodologically, all the previous researchers used the datasets[1,3,16,18,23,25] of DR, age-based, and gender-based related to internal eye disease. Here, in this article, Ethiopian datasets[12] of external eye disease images and public fundus images were used and evaluated. Technically, the model tools, whether vgg16, vgg19, or vgg34, and ResNet-X vary in speed depending on size and dropout (if used) to receive the scale of performance. Performance also depends on the basis of data size, system structure, and configuration. It shows that the lower version of the CNN model may produce better result than the higher version. Hence, it achieved an identification result of 98.48% with a 0.976% multiclass classification.

4 Conclusion

This research aims to classify blepharitis, cellulitis, and conjunctivitis using multiclass classification and identification of external eye diseases. The research achieved the objective using an efficient AI-based model for the settled purpose using taken datasets. Thus, new techniques are used to identify the external eye diseases in the mentioned category that have not been touched yet using CNN. The Vgg-16 model is utilized for the multiclass classification of images, which is a deep convolutional neural network. The model is run for two different dropout rates, and it attains the highest accuracy of 71.54% with a 0.50 drop-out rate with the 80-20 ratio deviation of the dataset. The evaluation matrix and cross-validation of R^2 are scrutinized to test the strength and performance of the model. It produces an accuracy of 98.48% and 0.976% for deep CNN and multiclass classification, respectively, which is a satisfactory result. The evaluation of MSPE was observed, and the efficiency of R^2 was evaluated with multiple classes of data that resulted in a range of 0.425 - 0.775 when k = 10 folds were tested. The effects of fundus in the ocular, such as retinopathy and AMD, can be examined in the future with segmented data using CNN for better optimization. On account of biological changes in eye and retinal structure, models might be constructed or studied.

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