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KERATOCONUS DETECTION USING DEEP LEARNING

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ABSTRACT

The eye is considered as one of the most complicated organs of the human body, with various ailments that can impact it. Eye diseases are any condition that disrupts its function, leading to vision problems or blindness caused by genetics and aging to injuries, infections, and environmental factors. Keratoconus is a condition where the cornea becomes thinner and bulges out, causing vision and visual impairment, and must be detected early to prevent potential complications. This paper used real data taken from TOMEY TMS-5 to build a dataset for convolutional neural networks (CNNs) GoogleNet algorithms to classify either a Keratoconus or a normal case. The suggested models provided correct decision up to 85% accuracy which is a good result compared to other approaches using raw data to avoid limiting decision to some parameters. The built dataset contains a group of patients (females and males) whose ages ranged from 14-75 years.

KEYWORDS

Keratoconus case, Convolutional neural networks (CNNs), MATLAB, GoogleNet.

1. INTRODUCTION

Eye disease are considered one of the main causes of poor vision and blindness. Early detection and treatment of these diseases assist avoid vision loss. Keratoconus is one of the eye diseases that occurs due to a developing disorder in the cornea that affects its structure and curvature, leading to distorted vision. Serious complications may occur if left untreated. Therefore, accurate diagnosis and timely treatment are extremely important. However, access to eye care is limited in many parts of the world in rural areas and developing countries.

Advances in machine learning(ML) and DL have shown promising results in data analysis including classifying medical illnesses from image data. CNNs are a type of DL algorithm that has proven effective in image classification and that can be trained on large datasets of images to learn to identify specific features that can be used to classify the images into different categories (LeCun et al., 2015; Shoieb et al., 2016).

Regularly of our study, the classification of eye diseases using DL has made significant contributions to the field of ophthalmology and medical diagnosis. Through DL, it is possible to identify precise signs of keratoconus at an early stage, which is crucial for timely intervention and helps improve patient outcomes, including planning appropriate treatment strategies, such as corneal cross-linking or contact lens fitting. the scalability of DL solutions makes it possible to deploy keratoconus detection tools globally, thus improving access to high-quality eye care and reducing the prevalence of undiagnosed cases of keratoconus, which would lead to fewer diagnostic errors, and helping remote patients receive their medical treatment at a lower cost and reduced pressure on medical staff.

2. LITERATURE REVIEW

Li, F. et al. applied optical coherence tomography (OCT) images to Multi-ResNet50 assembling to detect choroidal neovascularization (CNM) and macular edema (DME). Excellent categorization accuracy and performance were achieved using the suggested strategy (Li et al., 2019). Kuo, B. et al. detected the pattern difference between keratoconus and normal eyes using three widely known CNN models, ResNet152, VGG16, and InceptionV3. These networks achieved an accuracy of 0.90 to 0.995 (Kuo et al., 2020). Bernabe, O. et al. presented a unique intelligent pattern of classification algorithm based on a CNN for classifying retinography images of glaucoma and diabetic retinopathy. This algorithm achieves a high accuracy percentage of 99.89% in classifying eye diseases (Bernabé et al., 2021). Dipu, N. et al. developed ResNet-34, Efficient Net, MobileNetV2, and VGG-16 models for classifying eye diseases based on neural networks. In this work, VGG-16 achieved the greatest accuracy of 97.23% (Dipu et al., 2021).

Guo, C. et al. have used a lighter DL architecture named MobileNetV2 to distinguish between four common eye diseases, which are pathological myopia, maculopathy, retinitis pigmentosa, and glaucoma. the proposed approach achieved high levels of sensitivity, specificity, and accuracy (Guo et al., 2021). Mahmoud, H. et al. provided a strategy for detecting the keratoconus through the generation of 3D eye images from 2D frontal and lateral eye photos, which included extracting geometric features from 2D images to estimate depth information. which was utilized to create 3D images of the cornea. This study produced a 97.8% diagnostic accuracy, 98.45% sensitivity, and 96.0% specificity (Mahmoud et al., 2021). Feng, R. et al. used the KerNet DL technique in order to identify keratoconus and subclinical keratomas. This technique concentrates primarily on locating areas with subclinical keratoconus. High levels of accuracy are achieved by the suggested technique (Feng et al., 2021). Lavric, A. et al. have created several machine-learning models to identify keratoconus through the measurements of corneal elevation, pachymetry, and topography, which were collected from 5881 eyes of 2800 Brazilian patients using a PENTACAM SCHEIMPFLUG device (Lavric et al., 2021).

Zaki, W. et al used the VGGNet 16 model to detect keratoconus disses, which achieves an accuracy of 95.75%, a specificity of 99.25%, and a sensitivity of 92.25% (Zaki et al., 2021). William, F. et al. have used CNN models for classifying eye states (open or closed) using EEG data. The temporal ordering of the EEG data was maintained, and multiple CNN network models were applied to both subject-dependent and subject-independent EEG classifications. this resulted in an accuracy of 96.51% on dataset I and an accuracy of 100% on dataset II. CNN models are effective for subject-dependent and independent eye state classification; their best accuracy rates are 96.51% for subject-dependent and 80.47% for subject-independent (William et al., 2021). Degadwala, Sh. et al. suggested a CNN-based automated technique for detecting and classifying eye melanoma cancer with a high accuracy rate of 92.5%. An automated technique to identify the skin of the eye using a CNN with a gray victimization conversion to top image resolution is introduced (Degadwala et al., 2021). Tripathi, P. et al. developed a unique method that uses near-infrared eye pictures to diagnose cataracts, which is less expensive and simpler to use than an ophthalmoscope setup for data collection. High classification performance is achieved through a DL-based network (Tripathi et al., 2021). Subramanian, P. et al. employed CNN to classify keratoconus by segmenting and index-quantifying images of the eye topography. Results reveal that for a 3-class classification that includes mild keratoconus or form-fruste keratoconus, the method performs with an accuracy of 95.9% (Subramanian and Ramesh, 2022).

Farooqui, A. et al. suggested a simpler, more precise, and quicker deep neural network model used for early detection of the same eye disease, such as cataracts, diabetic retinopathy, and glaucoma (Farooqui et al., 2022). Erdin, M. et al. used CNN for early detection of eye diseases including trachoma, conjunctivitis, cataracts, and healthy eyes, with an accuracy of 88.36% (Erdin and Patel, 2023). Du F et al. proposed a model decision fusion method based on the D-S theory. and apply it to the decision fusion of eye disease recognition models. This model achieved an accuracy of 0.9237 (Du F et al., 2024). Mohamed, E et al. proposed to apply OCT to a CNN on retinal images to extract features that allow early detection of ophthalmic diseases. This work achieved higher accuracy that was used to classify the dataset to normal retina, DME, CNM, and Age-related macular degeneration (AMD) (Mohamed and Marwa 2024). Faizur, R. et al. proposed a novel and unique model that achieved an accuracy of 98.48% to classify external eye diseases like blepharitis, conjunctivitis, and cellulitis by using CNN, and Vgg16 (Faizur 2024).

3. PROBLEM STATEMENT

The critical phase of identifying keratoconus is a crucial task to avoid any disease progression that might occur, including the possibility of vision loss. Many techniques have been evolved to detect eye illnesses using reliable medical images. However, classification and segmentation of the data is considered one of the most fundamental and challenging tasks. The most important challenges are:

- The rate of classification error must be as low as possible.
- The essential need for a huge amount of data.

These points represent the main challenges that pushed us to research the segmentation and the classification.

4. METHODOLOGY OF DATA PREPARATION

The initial step in the classification process using DL is a crucial stage that includes selecting and preparing the data to suit the network being used. Fig. 2 illustrates the methodology employed for this purpose.

4.1. Dataset collection

A dataset of labeled medical images was assembled. This dataset included images of patients' eyes with and without the disease of interest to aid disease categorization. Knowing that the wider and more diverse the dataset, the better the CNN can learn to generalize and predict accurately. The images utilized as a dataset in this research were collected from the Um Al-Rabi'ein clinic (Mosul, Iraq), with 400 cases (200 of which are healthy cases and the rest are affected cases).

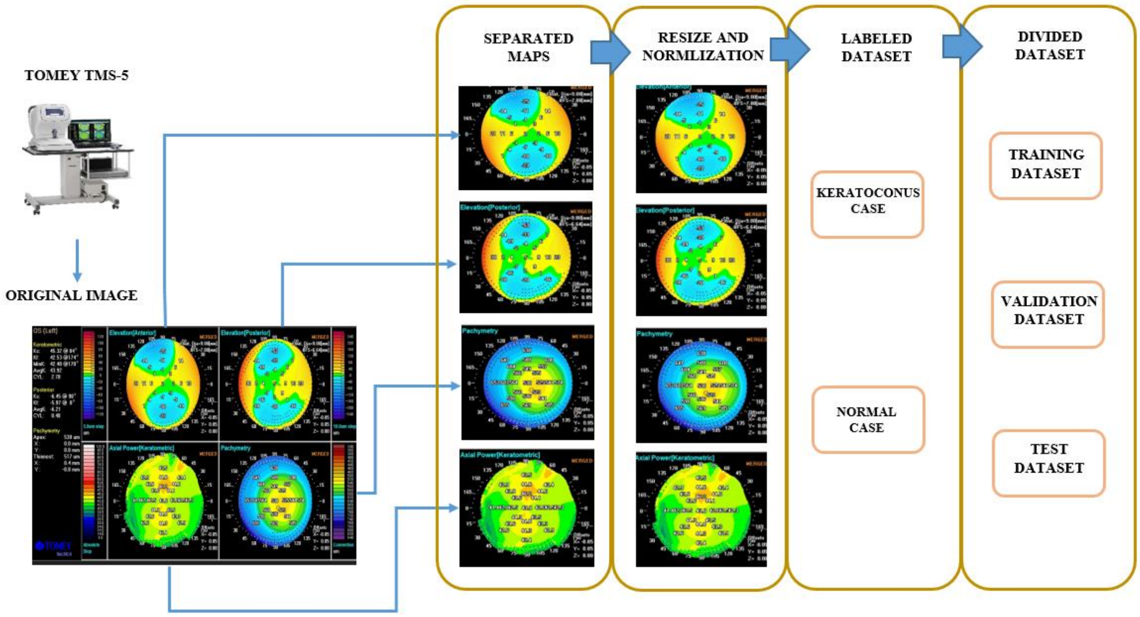


Fig. 2. Data Preparation steps

4.2. Data preprocessing

Image preprocessing is critical in ensuring data quality, resulting in more reliable and accurate models. Various preprocessing techniques are employed to prepare medical images before feeding them into a CNN to enhance the model's performance. Using a MATLAB function, several preprocessing techniques were applied to the dataset, including:

- Resizing: When using any type of dataset to train a specific network, it is crucial to ensure the dimensions of the images and the size of the data handled by the CNN are appropriate. This technique helps adjust the size of the images to match the requirements of GoogleNet by converting them to dimensions of 224 × 224 pixels.
- Normalization: To ensure the stability of the training process and to accelerate model convergence, it is important to have pixel values on a comparable scale. This can be achieved using normalization techniques to scale pixel values to a range between 0 and 1.

Finally, the dataset has been labeled (Keratoconus case, and Normal case) and then divided into three sets: the training set, which is used to train the model, and the validation set, which is used to tune hyper-parameters. and the testing set, which is used to assess the final performance of the model. An illustration of the dataset details is summarized in Table 1.

Table 1. Details of the dataset

Data	Specification
source's dataset	the Um Al-Rabi'ein clinic
images size	224 x 224
Number of classes	Binary
Name of Classes	Keratoconus case, Normal case
Training dataset	80% of the overall dataset
Validation dataset	20% of the overall dataset

5. THE PROCESS OF TRANSFER LEARNING

5.1. Building the GoogleNet CNN model:

GoogleNet was chosen for the classification of keratoconus disease because it outperformed other types of CNNs in medical image classification. Additionally, it has been demonstrated that the weights learned by GoogLeNet are distinguishable, effectively capturing edge-like features. Finally, its ability to retain most feature maps through various convolutional layers has proven to enhance its performance in medical image analysis (Alsharman and Jawarneh, 2020). This network's model, as illustrated in Fig. 3, was supposedly developed using the ImageNet dataset as well as millions of common object pictures from a large dataset to account for high feature representations (Krizhevsky et al., 2012). It can recognize patterns in around a thousand images. This model, like other neural networks used in computer vision applications, accepts images as input and returns labels for one of its learned classes, as well as the confidence level (Santos, 2020). GoogLeNet's architecture has 22 layers and 9 inception modules, with learnable filters ranging in size from (1x1) to (5x5). Convolution is done in parallel to capture characteristics at different levels of detail (Szegedy et al., 2015).

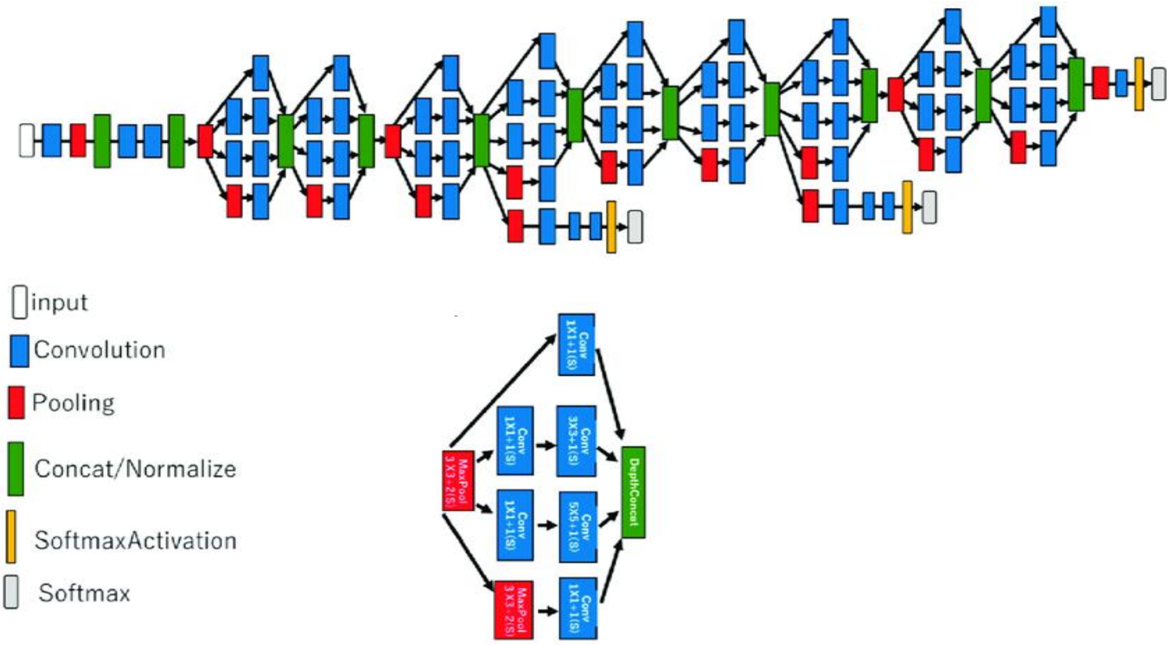


Fig. 3. The architecture of GoogLeNet (Matsuzaka and Uesawa, 2023)

5.2. Model re-training

During the training process, the CNN learns to optimize its internal parameters (weights and biases) to minimize a chosen loss function. Commonly used loss functions for classification tasks include categorical cross-entropy or binary cross-entropy, depending on the number of classes (binary or multi-class classification). Finally, the model was re-trained on the

Keratoconus dataset using the training set. The process of transfer learning is illustrated in Fig.4.

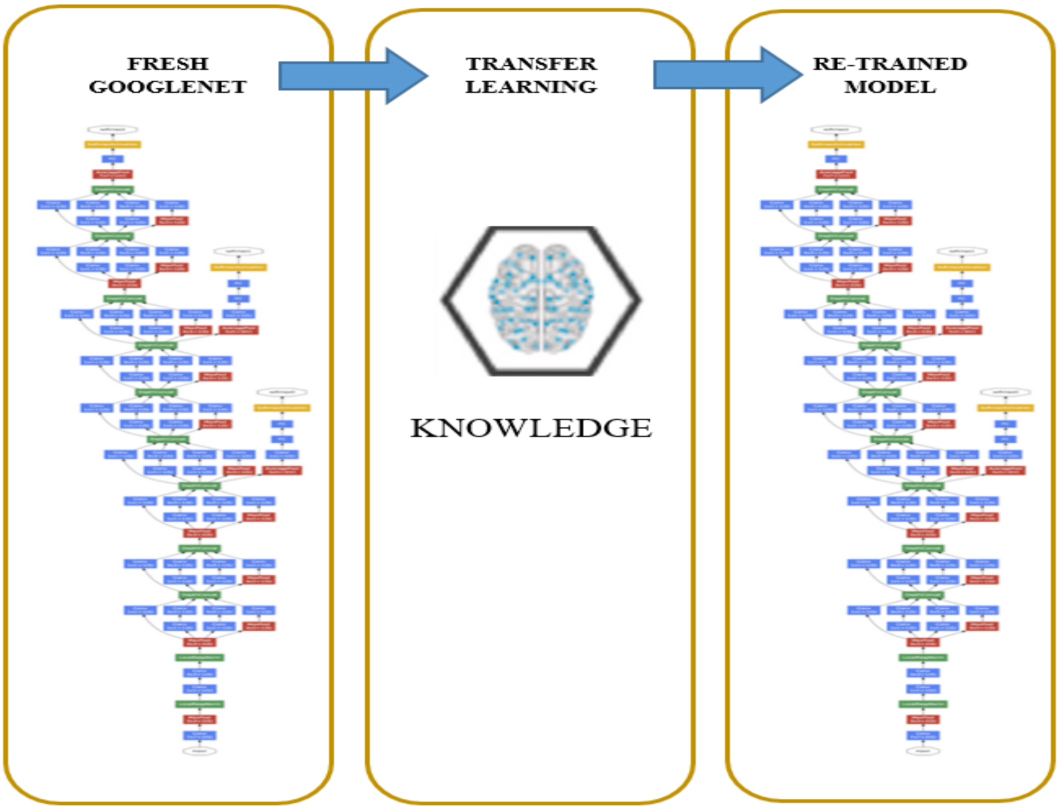


Fig. 4. The process of transfer learning

5.3. Training evaluation

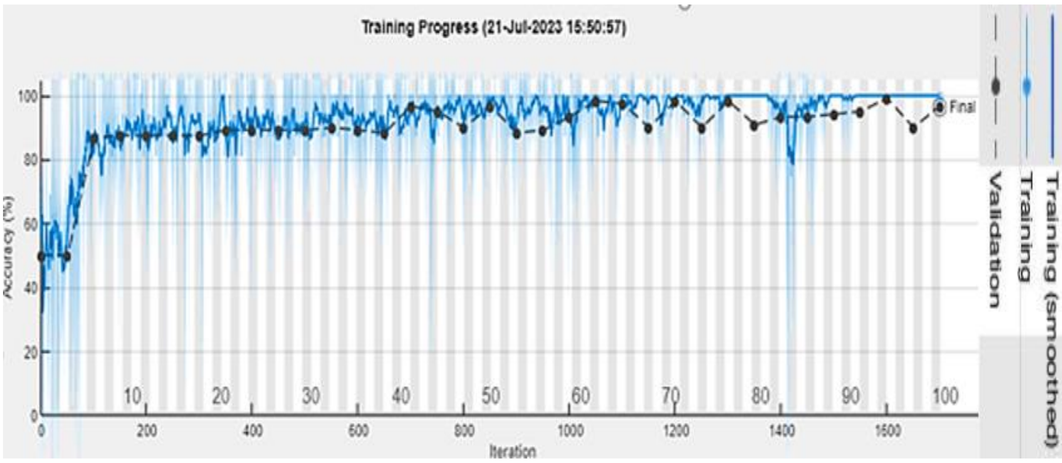
An evaluation was made for the model's performance based on checking the results' accuracy. Thus the training options in the Matlab DL apps had to be changed, therefore many different learning rates, batch sizes, and training periods have been tried to get the highest possible accuracy. Table 2 shows the parameters of the training process. The stochastic gradient descent with momentum (SGDM) algorithm assists in accelerating convergence by using momentum to facilitate gradient updates. Additionally, it avoids the pitfalls of simple gradient descent, such as getting stuck in local minima and slow convergence. initial learning rate is 0.0001 and this small value especially important for complex models or sensitive tasks like medical image analysis, where precision is crucial, chosen to ensure that the model learns gradually and the updates to the weights are small and stable. A batch size of 128 strikes a balance between computational efficiency and the stability of gradient updates. The value of epochs affects the network's learning, so training for 100 epochs was chosen to certify the model learns comprehensively from the data. The maximum number of 1700 iterations confirms detailed and extensive training. Frequent validation every 50 iterations provides regular feedback on performance. Training on a CPU demonstrates the model's ability to adapt to different computational environments, albeit with longer training times.

Table 2. Training parameters

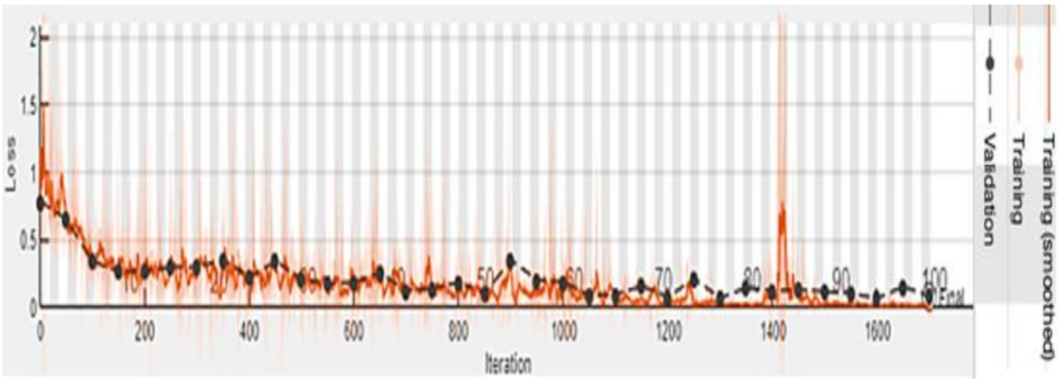
parameter	setting
Optimize algorithm	SGDM
Initial learn rate	0.0001
Min batch size	128
Max epochs	100
Max iteration	1700
Validation frequency	50
Execution environment	CPU

CNN has been used to predict the presence of Keratoconus. This CNN model demonstrated an accuracy of 96.6% where the training parameters of GoogleNet in which the Keratoconus dataset was used, are shown in Fig. 5, indicating its potential as a useful way for Keratoconus detection and diagnosis. The high accuracy of this CNN model reveals its capacity to successfully distinguish between healthy and Keratoconus-affected eye. Despite efforts were made to reduce such biases, more validation on more diverse and larger datasets is advised for robustness. Although professional ophthalmologists thoroughly labeled the photos, the availability of ground truth labels for Keratoconus diagnosis in the dataset could be prone to errors. Future research should strive for more comprehensive and accurate labeling for training purposes. Fig. 6 shows the accuracy and the losses for training CNN.

Fig. 5. The parameters of training the GoogleNet CNN model using the keratoconus dataset.



(i)



(ii)

Fig. 6. Evolution of training/validation of GoogleNet CNN model toolbox over 100 epochs and 1700 iterations: (i) accuracy; (ii) loss

6. DATA CLASSIFICATION AND RESULTS

Finally, the system was ready to assess multiple cases, including diagnosed disease carriers and keratoconus-free. Thus the test dataset was used to observe the obtained results. To check the performance of the model a confusion matrix was used, which gives True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) parameters, which are critical for evaluating the accuracy of classification, recall, and precision using the following equations (Chicco and Jurman, 2020).

$$Accuracy = (TP + TN)/(TP + TN + FN + FP) \quad (1)$$

$$Recall(r) = TP/(TP + FN) \quad (2)$$

$$Precision = TP/(TP + FP) \quad (3)$$

$$specification = TP/(TP + FN) \quad (4)$$

$$FI - score = 2 * Precision * Recall/(Precision + Recall) \quad (5)$$

In **Fig. 7**, the confusion matrix shows that the proposed model has high true positive and true negative rates, further demonstrating its dependability and potency. Then, the model must have strong sensitivity and specificity since there are a limited number of FP and NP.

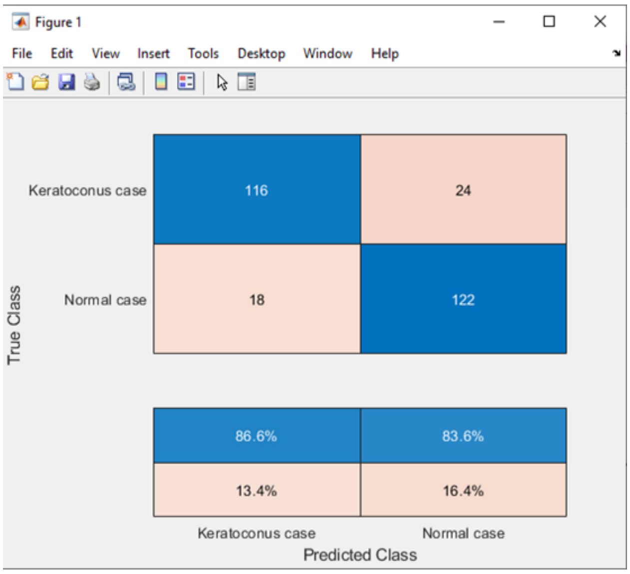


Fig. 7. The Confusion matrices of test data

According to Table 3, the effectiveness of the way keratoconus cases are classified can be seen in the methodology applied that involves dataset selection, network re-training, and classification. Several factors were determined from the confusion matrix information. Recall along with stable accuracy demonstrates high performance in detecting TP but also simultaneously keeping low FP rate. F1-score entertaining is an indication of the model's robustness since it has a good combination of precision and recall.

Table 3. Information of confusion matrix

parameter	value
Number of the test dataset	280
TP	116
TN	122
FP	18
FN	24
Accuracy	0.85
Recall	0.828
Precision	0.866
specification	0.87
F1-score	0.847

7. DISCUSSION

A series of studies conducted in the years 2023 and 2024 demonstrated that DL approaches were effective for diagnosing keratoconus. The research models are summarized in Table 3 and compared to the proposed approach. With Xception and InceptionResNetV2 DL, early clinical keratoconus was detected (Al-Timimi et al., 2023). To improve workload on medical personnel, computer-aided DL diagnostic model was developed to make clinical diagnosis more effective and support expert medical growth (Yan et al., 2023). A 3D modeling, using anterior segment optical coherence tomography (AS-OCT) data, extracted from the anterior corneal surface area and volume can differentiate between keratoconus and normal corneas (Tran et al., 2023). Hazem et al. utilized DL techniques to accurately classify keratoconus by identifying the changes in corneal dynamics (Hazem et al. 2024). When classifying diseases, MobileNet combined with a multilayer perceptron achieved a decent performance level (Lennart et al. 2024). As shown in Table 3 for multiple datasets used, the proposed method has excellent segmentation accuracy with minimal processing complexity. The critical steps taken during this research include

- The dataset included images of patients' eyes with and without the disease of interest to aid with disease categorization
- Implement GoogleNet to display high rankings Efficiency.
- Achieving an accuracy rate of 85% in the proposal classification.
- Calculate Accuracy, F1 Score, Recall, specification**,** and Precision by plotting confusion matrices.

Table 3. Comparison between the proposed method performance and the previous work

Author	Dataset	Classification	Accuracy	Model
Al-Timemy et al., 2023	The dataset consisted of corneal maps acquired with the Pentacam instrument in Egypt and Iraq	normal, suspect, and established keratoconus cases	88%-100%	Xception and InceptionResNet V2
Yan et al., 2023	Renmin Hospital of Wuhan University and Zhongnan Hospital of Wuhan University.	normal or abnormal	91.4%-96.7%	DL
Tran et al., 2023	The dataset was obtained by identifying keratoconus patients and healthy control patients between the ages of 20 and 79.	keratoconus and healthy controls.	N/A	DL
Hazem et al.2024	From 734 patients	keratoconus and normal	89%	3DCNN
Lennart et al. 2024	From 570 patients	normal or abnormal	83%	MobileNet
Proposed Method	The Um Al-Rabi'ein clinic preparation by the authors	normal or abnormal	٨٥%	GoogleNet

8. CONCLUSIONS AND FUTURE WORK

This study reveals the successful implementation of a GoogleNet CNN model for the detection of keratoconus with an accuracy of 96.6%. The model's remarkable accuracy, together with the examination of various measures, underlines its promise as a dependable way for Keratoconus screening and diagnosis. These findings pave the way for future advances in ocular imaging-based diagnosis, providing new potential for early intervention and improved Keratoconus care. The future study on this approach is expected to include plans to add more samples to increase the size of the dataset and investigate other methods for improving early diagnosis of eye illnesses.

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