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DETECTION OF KERATOCONUS DISEASE DEPENDING ON CORNEAL TOPOGRAPHY USING DEEP LEARNING

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ABSTRACT

Keratoconus is a disease that ML has contributed much in its diagnosis and management. It is not a widely prevalent disease, with a research gap caused by the absence of standardized datasets for model training and evaluation. This work presents a novel dataset, which strengthens the CNN model's resilience and creates standards for assessing keratoconus diagnostic techniques. The research depends on data of patients examined at Jenna Ophthalmic Center in Baghdad. The proposed system works on three stages: pre-processing, feature extraction, and classification with machine learning algorithms including NB, KNN, ADA, DT, and CNN deep learning. The pre-processing stage involves cropping images to retain the relevant maps, which were subjected to contrast enhancement to improve image quality. The pre-processed data is then fed into Machine Learning(ML) algorithms and Convolutional Neural Network(CNN) models, by which the four corneal maps were analyzed. The precision of the ML method was quantified, yielding a precision score of 0.79 for the AdaBoost algorithm and an impressive score of 0.99 for the suggested CNN model exemplifying its high accuracy and ability to surpass all machine learning approaches. Applying PCA for feature extraction before utilizing tradition ML algorithms and CNN helps in achieving high-accuracy results.

KEYWORDS

Keratoconus, Corneal disorder, Irregular astigmatism, Convolutional Neural Network (CNN), Precision, Ophthalmic Center.

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1. INTRODUCTION

Keratoconus is a relatively uncommon degenerative disease affecting the cornea; the transparent dome-shaped anterior portion of the eyeball, where the cornea mainly its central and paracentral parts, under-goes progressive steepening and thinning causing changes in corneal curvature resulting in irregular astigmatism and a variable amount of scarring, and thus image blur (Mustapha Lachgar, Mohamed Hamid, Hrimech Kartit, 2021).

The exact cause is unknown but a positive family history has been reported. The prevalence of keratoconus is often reported to be 1 in 700 (Castro-Luna and Pérez-Rueda, 2020)(Gokul *et al.*, 2017). The cornea in keratoconus undergoes thinning of its stroma causing bulging and coning and different degrees of corneal scarring. Keratoconus usually affects both eyes but is often asymmetric. It typically starts in early adolescence and progresses into the mid-20s and 30s. However, progression is variable, and there is often a history of multiple changes in eyeglass prescription that do not completely restore vision. Decreased vision is caused principally by a corneal distortion-induced irregular astigmatism and myopia, and in later stages by corneal scarring.

By using a slit-lamp examination and observing a central or inferior corneal thinning, a diagnosis can be made. Cases may begin much earlier or later in life, and progression may also persist beyond the 30s.

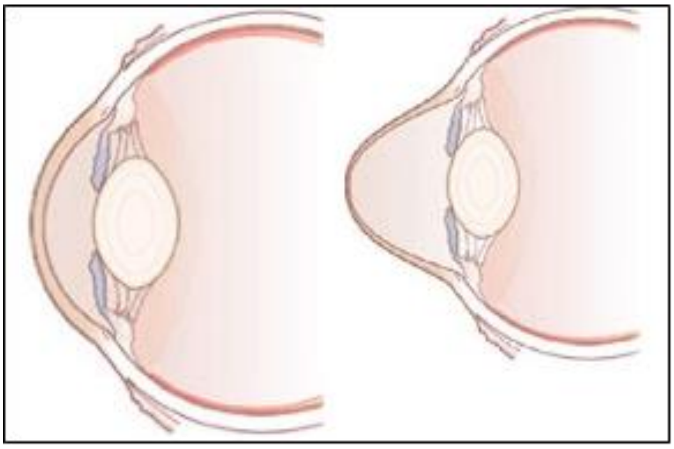

Fig. 1. Healthy cornea keratoconus cornea
(Mustapha Lachgar, Mohamed Hamid, Hrimech Kartit, 2021)

Computerized videokeratography can be used to track the development of keratoconus and is helpful in its early detection. The thinnest region of the cornea can also be measured using ultrasound pachymetry. With the development of new algorithms based on computerized videokeratography, subclinical or suspected keratoconus can now be identified (Gokul et al., 2017). Over the years Various Machine-learning approaches have been developed to diagnose keratoconus and screen patients for refractive surgery (Abbass et al., 2022). These systems use neural networks, support vector machines, and automatic decision trees to analyze corneal imaging data from several devices (Bolarín et al., 2020)(Lin et al., 2019). Comparing these studies directly is challenging because keratoconus encompasses a broad range of illnesses. More significantly, there is no publicly available dataset available for study. Despite these obstacles, the field of machine learning for keratoconus detection and screening for refractive surgery is growing and has a lot of potential for future development as imaging techniques become more sophisticated (Bolarín et al., 2020). The research aims at building a CNN model based on a fairly small amount of data for early detection of keratoconus.

This study is a mono-center study that includes 200 patients who underwent corneal examination using a Galilei corneal imaging machine which, unlike most studies that depend on just a Scheimpflug imaging system from a pentacam camera, combines the advantages of two technologies: high accuracy curvature data of Placido disc-based corneal imaging with precise elevation data from Scheimpflug technology.

This study is organized as follows: a thorough study of the literature, a description of the experimental design, an explanation of the experiment's findings, and a conclusion.

2. LITERATURE REVIEW

High diagnostic accuracy and clinical interpretability have been demonstrated by a study comparing deep learning algorithms for keratoconus identification using corneal topography pictures. Images from 170 keratoconus patients, 28 subclinical keratoconus patients, and 156 control subjects were used by the researchers. High sensitivity and specificity were attained by the models; the ResNet152 model even scored an excellent AUC-ROC of 0.995. With future studies examining more datasets and more complex learning architectures, these models may enhance patient treatment and results (Kuo et al., 2020).

Using corneal topographic maps and four pre-trained networks, the paper introduces an Ensemble of Deep Transfer Learning model for clinical keratoconus (KCN) detection. With average accuracies ranging from 86% to 89.9%, the model occasionally obtained individual accuracies above 90%. The accuracy of deep classifiers based on corneal maps was increased to 92.2% and 93.1%, respectively, via the ensemble approach. The results point to advancements in the creation of a computer-assisted diagnosis system for the treatment of KCN (Al-Timemy et al., 2022).

Several machine learning models had been developed by Alexandru Lavric and Liliana Anchidin who studied 5881 eyes of 2800 keratoconus Brazilian patients examined by a Pentacam Scheimpflug instrument using three parameters: corneal elevation, topography and pachymetry. The highest accuracy in distinguishing normal from keratoconus cases was provided by elevation parameters with an area under the curve (AUC) of 0.99, and in detecting different severity keratoconus levels with an AUC of 0.88. The developed algorithm can differentiate with high accuracy eyes with early keratoconus from healthy eyes with an AUC of 0.97. Clinically, it is crucial to detect patients with early keratoconus because early symptoms in these patients are usually misdiagnosed (Lavric et al., 2021).

In 2022 a Convolutional Neural Network(CNN) was developed by Jan Schatteburg and Achim Langenbucher to diagnose Keratoconus. The datasets were collected from more than 1900 keratoconus patients in the keratoconus center of the eye clinic of Homburg University Hospital. Initially. The thickness maps were used on which the CNN was executed. This process is intended to be repeated for curvature and elevation maps if the program performs excellently and the accuracy is found to be more than 80%. Later a run with augmented data that included subclinical keratoconus was done. Finally, the neural network was fed with dataset of normal eyes, eyes with fully manifested keratoconus, and eyes having other corneal diseases (Schatteburg and Langenbucher, 2022).

In a study conducted at three centers; namely: Royal Liverpool University Hospital (Liverpool, UK), Sedaghat Eye Clinic (Mashhad, Iran), and The New Zealand National Eye Center (New Zealand), a CNN model was proposed to distinguish between keratoconus and healthy eyes. This CNN model was trained and tested using corneal tomography scans which were classified depending on Amsler-Krumeich classification. Each scan consists of four maps: axial map, anterior and posterior elevation map, and pachymetry map. A testing set of scans from the Sedaghat Eye Clinic in Iran was utilized The CNN succeeded to diagnose keratoconus corneas at an accuracy of 0.9785 on the testing set (Chen et al., 2021).

A summary of the above three works are shown in Table 1 below:

Table 1. Summary of the reviewed works

Title of Articles	Methods	Advantage	Disadvantage	Accuracy Percentage
Keratoconus Screening Based on Deep Learning Approach of Corneal Topography	VGG16, Inception V3, ResNet152	Adaptability across different imaging platforms, Automated pattern recognition without manual input	Limited generalizability due to single-institution data	0.93, 0.93, 95
Deep Transfer Learning for Improved Detection of Keratoconus using Corneal Topographic Maps	EDTL with AlexNet and product fusion	Effective use of transfer learning reduces the need for large datasets	Limited interpretability, as combining multiple models adds complexity in understanding decision paths	0.983

Keratoconus Severity Detection from Elevation, Topography, and Pachymetry Raw Data Using a Machine Learning Approach (Lavric *et al.*, 2021)	Machine Learning Algorithms (DT, SVM, KNN, discriminant, Ensemble)	Using a large subset of real world data implementation pre-processing on date 2 classification tasks were performed	When the number of classes increases, the accuracy of most machine learning models decreases.	0.97
Protocol for the diagnosis Of keratoconus using convolutional neural networks (Schatteburg and Langenbucher, 2022)	Deep learning (CNN)	Using the most promising tool in diagnosis across all of Medicine(CNN) Using a real dataset	Classify data as either "healthy" or "keratoconus" The model is not generalizable	More than 80%
Keratoconus detection using deep learning of color-coded maps (Chen *et al.*, 2021)	Deep learning (CNN)	2 classification tasks were performed using two real datasets Using an efficient pre trained network	No implementation of image processing techniques	99.07% in binary classification 93.12% in multi-classification

3. METHODOLOGY

A new CNN model is designed which, unlike traditional CNNs, can deal with only small amount of real data that had been treated previously with PCA giving high accuracy results.

This proposed system works on three stages: pre-processing which include (cropping, convert colored images into greyscale images, histogram equalizer, resizing), feature extraction, and classification with machine learning algorithms including NB, KNN, ADA, DT, and CNN deep learning. The proposed system's block diagram is shown in Fig 2.

3.1. Datasets

The data was derived from patients who had been examined at Jenna Ophthalmic Center in Baghdad/Iraq and had been tested using The Galilei™ Dual Scheimpflug Analyser (Ziemer Group; Port Switzerland), which is a relatively new device for corneal and anterior segment evaluation. The analysis relies on corneal topography based on Placido-disc principle and a dual Scheimpflug anterior segment imaging. The integrated system takes advantages of both technologies in a single exam, using a common reference axis (Piñero, 2016).

Every image consists of four maps: Axial curvature, Corneal thickness, Anterial elevation, and Posterior elevation maps, which are shown in Fig. 3 a without keratoconus, b with keratoconus.

✓ The four maps represent pictures of the central 9mm of the cornea

✓ The numbers on the X and Y axes represent the distance in millimetres from the central (0) horizontal and vertical meridians; the positive (+): towards the right, the negative (-): towards the left

✓ The colour in the maps represent codes to simplify their interpretation. They are ranging from warm (red, orange, yellow), neutral(green), to cool colours (blue, purple). In curvature maps(a) steep parts of cornea represented by warm colours while flat ones are cooler. In thickness maps(b) warmer colours indicate thinner areas and cooler colours marks thicker parts. Maps c and d represent changes of elevation in anterior and posterior corneal surfaces where warmer colours refer to areas that are elevated above the normal while cooler ones indicate areas depressed below normal

✓ The numbers inside each map are values of different locations in the cornea, with units specific to each map:

- Axial curvature: the unit is in dioptre of curvature (D)
- Anterior elevation BFS: the unit of thickness is in micrometers (µm)
- Posterior elevation BFS and Corneal thickness: the units are in micrometers (µm)

The Data set consists of corneal topography images of 400 eyes; 200 keratoconus eyes (100 patients), and 200 non-keratoconus eyes (100 normal persons). Table 2 shows the data distribution of keratoconus-related images across training and testing datasets.

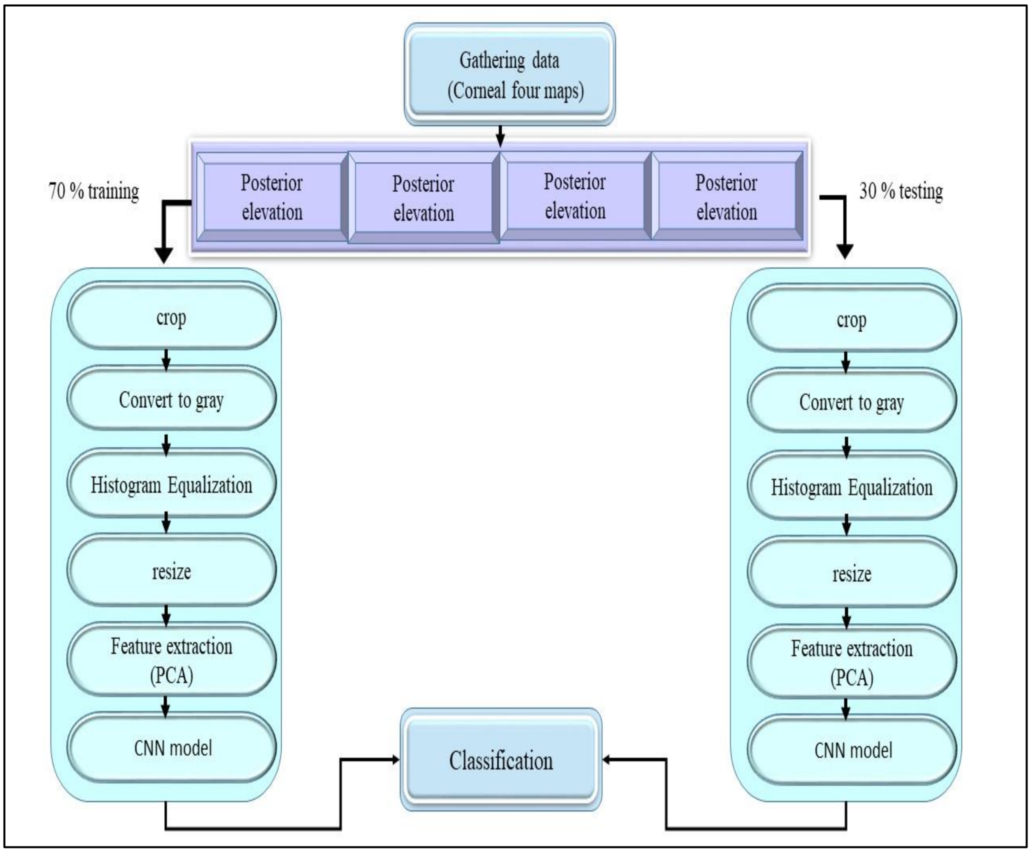

Fig. 2. Block Diagram of the proposed system

a **b**

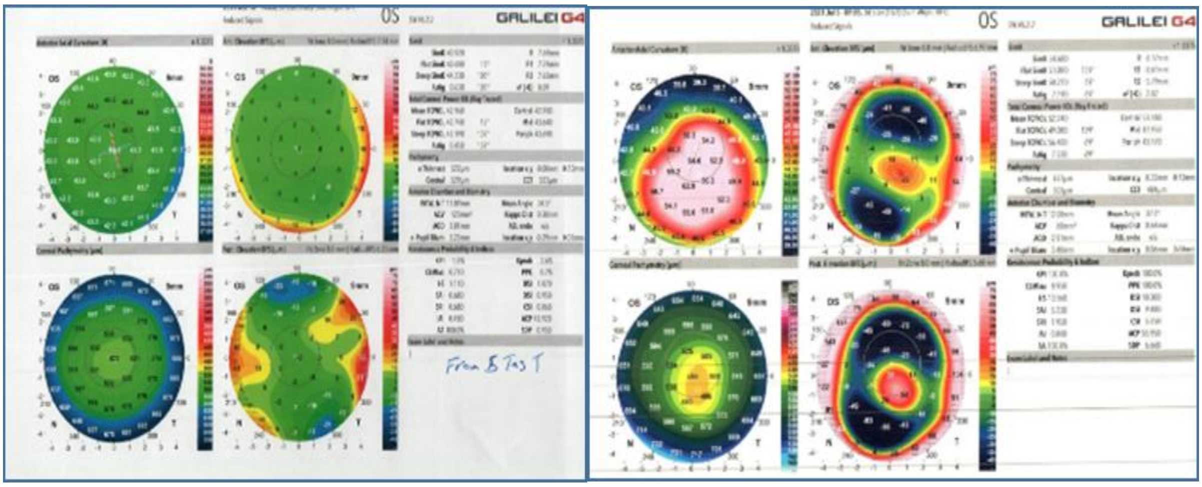

Fig. 3. (a) Without keratoconus; (b) With keratoconus

Table 2. Data distribution of keratoconus

Classes of corneas	Number of Patient	Number of Image	70% Training Image	30% Testing Image
With Keratoconus	100	311	218	93
Without Keratoconus	100	217	152	65
Total	200	528	370	155

3.2. **Pre-Processing**

3.2.1. Cropping

selecting and extracting a specific four map from a corneal image, Define the coordinates and dimensions of the region of interest (ROI): top-left corner coordinates (x, y) and the width (w) and height (h) of the desired crop(ROI) Table 3 and Fig.4 shows Cropping four map from original image

Table 3. Coordinates and dimensions of the region of interest for four maps

Map number	Top-left x coordinate	Top-left y coordinate	Width of the ROI	Height of the ROI
Map1	60	150	300	400
Map2	360	150	300	400
Map3	60	550	300	400
Map4	360	550	300	400

a **b** **c** **d**

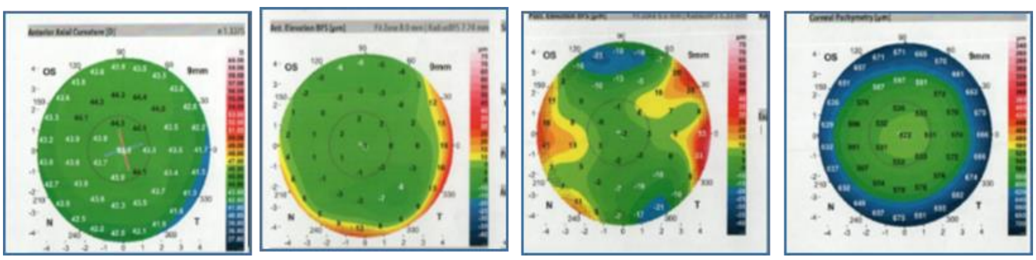

Fig. 4. a-b-c-d The four cropped maps

3.2.2. Grayscale

converted cropped coloured images into greyscale images make the image takes less storage space and fewer channels in representation (Bala and Braun, 2003). Fig. 5 shows 4 map images converted to greyscale colour space. The following equation is used to convert an image from RGB to grayscale.

$$\text{GRAY} = 0.30\ \text{R} + 0.59\ \text{G} + 0.11\ \text{B} \tag{1}$$

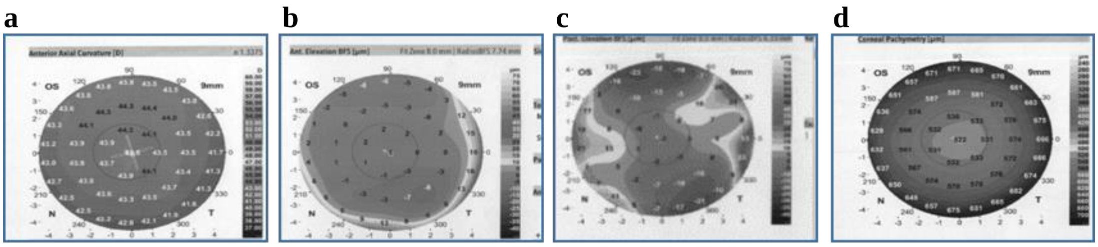

Fig. 5: a-b-c-d The four greyscale maps

3.2.3. Histogram Equalization

Histogram equalization is a spatial domain method that provides an output image with a uniform distribution of pixel intensity. It is typically increased the overall contrast of many images, especially when the relevant image data is represented by an adjacent contrast value.

The adjustment makes it possible for the histogram's intensity distribution to be more precise, allowing for places with low local contrast to have a higher contrast (Qi et al., 2022)(Alhakam and Salman, 2022). Convert the corneal image to grayscale with intensity levels ranging from 0 to 255, then apply histogram equalization to enhance image contrast (returns the equalized image). Fig. 6 shows corneal topography images after applying histogram equalization.

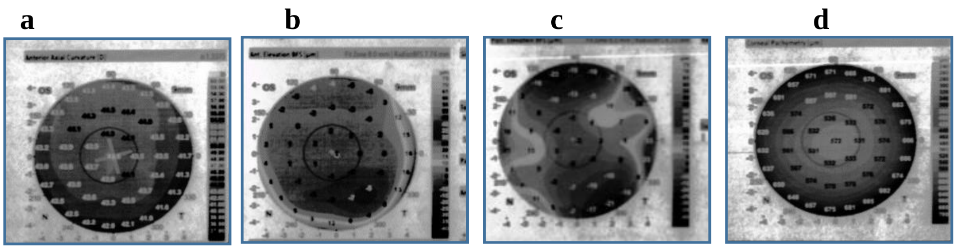

Fig. 6. a-b-c-d The four maps after applying histogram equalization

3.2.4. Resizing

The final important step in computer vision preprocessing is image resizing, since deep learning models typically train faster on small images (Saponara and Elhanashi, 2022). One method for scaling images is interpolation. Using the values of the nearby pixels as a guide, image interpolation aims to get the best estimate of pixel colour and intensity. In our work each image has been reduced to a 20 by 20 size.

3.3. Feature Extraction

Feature extraction phase is important for the process of dimensionality to lessen the complexity of the space and time needed for machine training. It is performed by extracting a subset of relevant features from the original data using a series of rules (Ebied, 2012) (et al., 2022).

In this work, Feature extraction is done by using Principle Component Analysis(PCA). The PCA is an effective feature extraction method in the pattern recognition field. Its goal is to describe the pattern with fewer quantities of features and to reduce the dimensionality of the feature space without losing the most important, for discrimination purposes, information (Liu and Wang, 2006).

Eigencorneal (Turk and Pentland, no date) built on the PCA techniques the strategy of the Eigencorneal method consists of extracting the characteristic features on the corneal and representing the corneal in question as a linear combination of the so-called ‘eigencorneal’ obtained from the feature extraction process (Karamizadeh et al., 2013).

$$Avarage = \frac{1}{M}\sum_{n=1}^{M} Training\ images\ (n) \tag{2}$$

$$Covariance = \sum_{n=1}^{M} sub(n)\ sub^{T}(n) \tag{3}$$

Where M: is the Training set of total images

μ: represent the average Mean

Sub: represent the subtracted image from the average μ

Using PCA for feature extraction before feeding the data to the CNN improves its suitability for the CNN model to learn from (Ren et al., 2017).

In the PCA method, the 2-Dimensional corneal image matrices need to be converted into a 1-Dimensional vector. This 1-Dimensional vector can be either a row or column vector. The main PCA steps for feature extraction in corneal images are:

1- Read corneal images and Make a training set of total M images to use them in computing the Average Mean as shown in the equation (2).

2- Subtract the original image from the Average Mean.

3- Calculate the Covariance Matrix as shown in equation (3).

4- Calculate the Eigenvalues and Eigenvectors of the Covariance Matrix.

5- Sort and choose the best Eigenvalues. The highest Eigenvalues that belong to a group of Eigenvectors are chosen; these M Eigenvectors describe the Eigencorneal.

6- Project the training samples onto Eigencorneal. And attain feature space.

3.4. The Classification Model

An especially suitable deep learning algorithm for tasks involving image recognition and processing is the convolutional neural network (CNN). It consists of several layers, such as fully connected and pooling layers in addition to convolutional layers (Abdulsalam, Alhamdani and Abdullah, 2019)(Al-dabbas, 2024).

The suggested CNN model consists of 28 layers: nine Convolutional layers of 1D, eight Leaky ReLU which are used as an activation function to have a good amount of features loaded to the CNN, six Max Pooling 1D layers for feature selection with valid padding to avoid reduction of feature numbers loaded to the CNN, four fully connected Dense layers for collecting, with same padding to keep some of features loaded to CNN and One Flatten layer. 1D Convolutional Layers are essential for the early identification of keratoconus because they can record sequential data patterns from corneal measurements (Alaa, Hussein and Al-Libawy, 2024). Max Pooling Layers Assure accuracy in corneal data analysis by reducing dimensionality while maintaining crucial details. Dense Layers Combine characteristics to forecast the existence of keratoconus accurately. Flatten Layer Facilitates efficient interpretation by preparing feature maps for dense layer processing.

Each layer includes filters, kernel size, strides, and padding (the number of pixels added to an image during CNN processing). The CNN models were trained across 100 epochs, Batch size 1024, Learning rate 0.001, Elapsed training time 3s 5ms/step, and Optimizer Adam.

To increase accuracy and efficiency, the CNN model for keratoconus detection uses 1D PCA. PCA lowers the computational load while maintaining important features by reducing the dimensionality of the data, which enables the CNN to concentrate on important patterns without overfitting. Data normalization, PCA application to capture significant variance, output reshaping for CNN compatibility, PCA-transformed data training, and performance evaluation are all steps in the workflow. The suggested CNN model is illustrated in Fig.7.

Compared to other general models, this model's design, especially focused on keratoconus, enables deeper corneal data analysis, enabling earlier and more accurate diagnoses. The testing is a dependable diagnostic tool in clinical settings, as evidenced by its higher accuracy and F1. The architecture of this CNN directly solves the difficulties associated with keratoconus diagnosis, enhancing the accuracy and effectiveness of ophthalmic diagnostics.

4. THE MEASUREMENTS AND RESULTS USING CNN DEEP LEARNING

The results obtained using CNN deep learning are shown in Table 4 and Fig. 8. In both classes, the CNN model achieves a precision, recall, F1-score, and accuracy of 0.99, indicating exceptional classification performance. The model exhibits good, consistent performance across all measures, classifying examples with 99% accuracy overall.

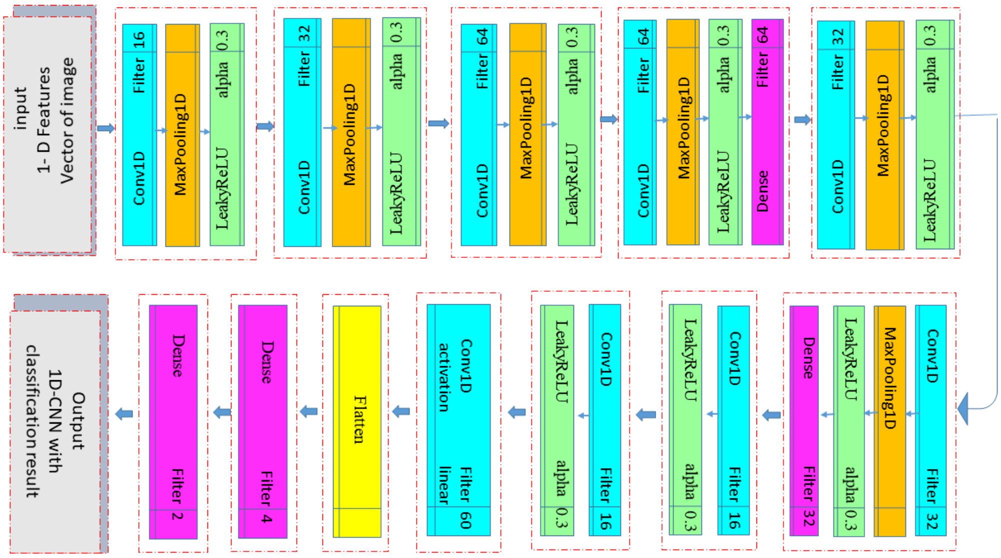

Fig. 7. CNN model architecture

Table 4. Results of proposed model using convolution neural network.

CNN	Precision	Recall	F1-score	Accuracy
Class 1	0.99	0.99	0.99	0.99
Class 2	0.99	0.99	0.99	0.99

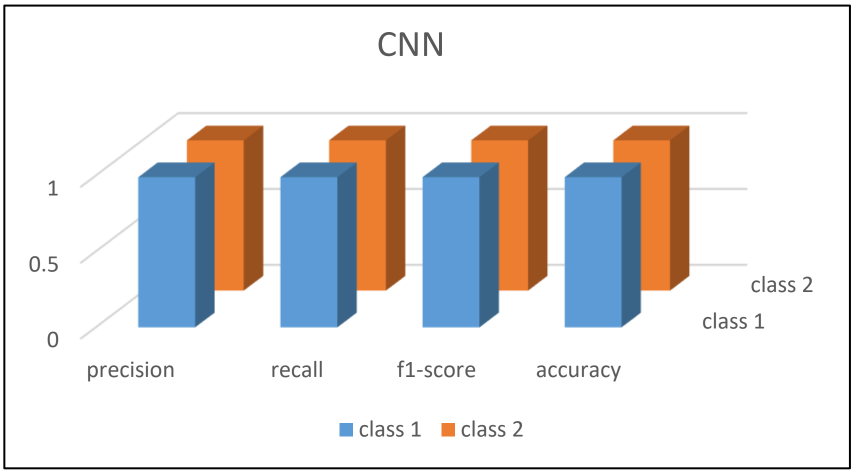

Fig. 8. Results of the proposed model using convolution neural network (calss1 = normal, class 2= keratoconus)

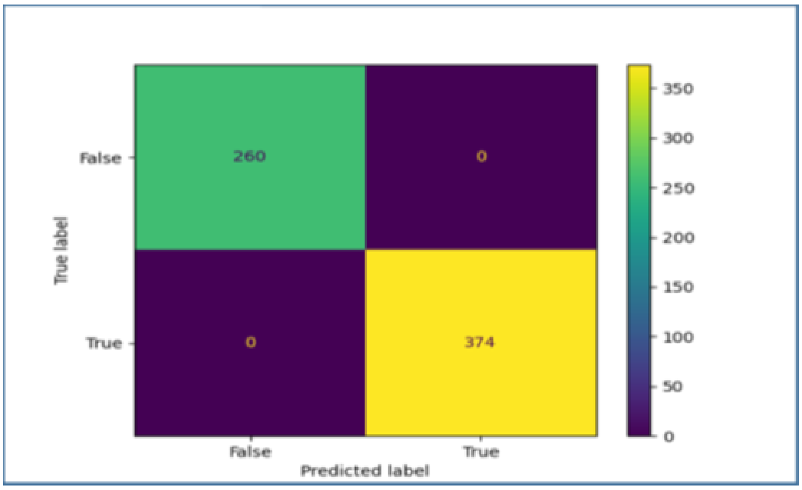

Fig. 9. The proposed system model's confusion matrix

4.1. Comparing Results of CNN versus ML Algorithms

Gathering data for keratoconus has proven to be challenging because the disease is not widely prevalent, and there is currently no standardized dataset available, unlike other image datasets (P and G P, 2022).Since dataset in this research is virgin and has not been used before, there were no works to be compared with, therefore Four machine learning (ML) algorithms, including Naive Bayes, k-Nearest Neighbours (KNN), Adaptive Boosting (AdaBoost), and Decision Trees (DT), were used to train the features and test them in order to compare the results produced to the results achieved using the CNN deep learning algorithm.

The Adaboost algorithem which is a function for learning clasification, removes nun beneficial characteristics from large set of them, reduce its final size (Al-Dabbas, Azeez and Ali, 2023). in our work among the four machine learning algorithms, AdaBoost algorithm achieved a relatively high accuracy of approximately 0.70 in identifying patterns related to keratoconus from ophthalmic images.

CNN deep learning yielded much better results compared to machine learning and this is clearly shown in Table 5 and Fig.10.

Table 5. Comparison between machine learning Methods and proposed model using convolution neural network based on results

Algorithm	Precision	Recall	F1-score	Accuracy
NB	0.67	0.66	0.65	0.656
KNN	0.63	0.62	0.63	0.623
ADA	0.72	0.71	0.71	0.709
DT	0.67	0.67	0.67	0.667
CNN	0.99	0.99	0.99	0.99

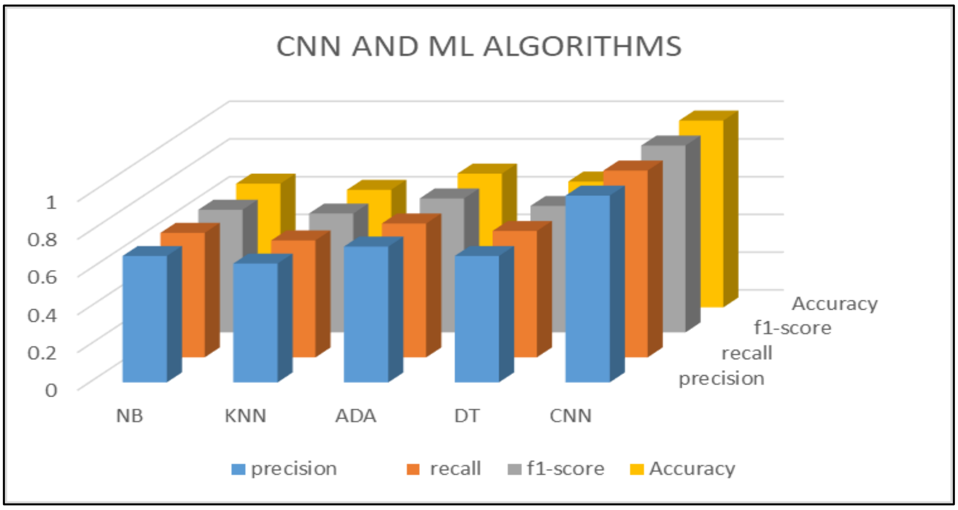

Fig. 10. Comparison between machine learning Methods and proposed model using convolution neural network.

Table 6 compares model performance for keratoconus detection. Prior models, like ResNet152, achieved high accuracy and recall, demonstrating effective detection. Among the proposed models, CNN excelled with precision, recall, F1-score, and accuracy of 0.99, highlighting its reliability and clinical applicability for accurate diagnostics.

Table 6. Performance of the suggested model compared to earlier research on the identification of keratoconus from corneal topography images.

Research	Algorithm	Precision	Recall	Accuracy
(Kuo *et al.*, 2020)	VGG16	-	0.917	0.931
	nceptionV3	-	0.917	0.931
	ResNet152	-	0.944	0.958
(Al-Timemy *et al.*, 2022)	(Net.3-EF, Net.4-EB, and LRSGD-PI)	-	0.86	0.931
	Net.1-SAG, Net.4-EB, and LRSGD-PI	0.983	0.966	0.983
	EDTL with AlexNet and product fusion	-	-	0.983
Proposed method	CNN	0.99	0.99	0.99

5. CONCLUSION

In conclusion, we suggest that to achieve high accuracy results while having a small sum of data, it can be very beneficial to apply 1D PCA for feature extraction before using convolutional neural networks (CNN) or traditional machine learning algorithms. The PCA with the CNN gives a perfect result with a 0.99 f1-score and accuracy in classifying corneal data, whereas in ADA the results of f1-score and accuracy were 0.71 and 0.709 respectively. To increase the keratoconus detection system's precision and practical usefulness, future research will combine data from several ophthalmic imaging devices and

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CONFLICT OF INTEREST

“The authors declare that they have no competing interests”.

6. REFERENCES

Aatila, M., Lachgar, M., Hamid, H., & Kartit, A. (2021). Keratoconus severity classification using features selection and machine learning algorithms. Computational and Mathematical Methods in Medicine, 2021(1), 9979560. doi: 10.1155/2021/9979560.

Abbass, A. A. et al. (2022) ‘Efficient Eye Recognition for Secure Systems Using Convolutional Neural Network’, Webology, 19(1), pp. 4967–4978. doi: 10.14704/web/v19i1/web19333.

Abdulsalam, W. H., Alhamdani, R. S. and Abdullah, M. N. (2019) ‘Facial emotion recognition from videos using deep convolutional neural networks’, International Journal of Machine Learning and Computing, 9(1), pp. 14–19. doi: 10.18178/ijmlc.2019.9.1.759.

Alaa, R., Hussein, E. A. and Al-Libawy, H. (2024) ‘Object Detection Algorithms Implementation on Embedded Devices: Challenges and Suggested Solutions’, Kufa Journal of Engineering, 15(3), pp. 148–169. doi: 10.30572/2018/KJE/150309.

Al-dabbas, H. M. (2024) ‘Two Proposed Models for Face Recognition : Achieving High Accuracy and Speed with Artificial Intelligence’, (April). doi: 10.48084/etasr.7002.

Al-Dabbas, H. M., Azeez, R. A. and Ali, A. E. (2023) ‘Machine Learning Approach for Facial Image Detection System’, Iraqi Journal of Science, 64(10), pp. 5428–5441. doi: 10.24996/ijs.2023.64.10.44.

Alhakam, I. and Salman, N. H. (2022) ‘An Improved Probability Density Function (PDF) for Face Skin Detection’, 63(10), pp. 4460–4473. doi: 10.24996/ijs.2022.63.10.31.

Al-Timemy, A. H. et al. (2022) ‘Deep Transfer Learning for Improved Detection of Keratoconus using Corneal Topographic Maps’, Cognitive Computation, 14(5), pp. 1627–1642. doi: 10.1007/s12559-021-09880-3.

Bala, R. and Braun, K. M. (2003) ‘Color-to-grayscale conversion to maintain discriminability’, Color Imaging IX: Processing, Hardcopy, and Applications, 5293(August 2014), p. 196. doi: 10.1117/12.532192.

Bolarín, J. M. et al. (2020) ‘A machine-learning model based on morphogeometric parameters for RETICS disease classification and GUI development’, Applied Sciences (Switzerland), 10(5). doi: 10.3390/app10051874.

Castro-Luna, G. and Pérez-Rueda, A. (2020) ‘A predictive model for early diagnosis of keratoconus’, BMC Ophthalmology, 20(1), pp. 1–9. doi: 10.1186/s12886-020-01531-9.

Chen, X. et al. (2021) ‘Keratoconus detection of changes using deep learning of colour-coded maps’, BMJ Open Ophthalmology, 6(1), pp. 19–22. doi: 10.1136/bmjophth-2021-000824.

Ebied, H. M. (2012) ‘Feature extraction using PCA and Kernel-PCA for face recognition’, 2012 8th International Conference on Informatics and Systems, INFOS 2012, (April).

Gokul, A. et al. (2017) ‘The natural history of corneal topographic progression of keratoconus after age 30 years in non-contact lens wearers’, British Journal of Ophthalmology, 101(6), pp. 839–844. doi: 10.1136/bjophthalmol-2016-308682.

Karamizadeh, S. et al. (2013) ‘An Overview of Principal Component Analysis’, Journal of Signal and Information Processing, 04(03), pp. 173–175. doi: 10.4236/jsip.2013.43b031.

Kuo, B. I. et al. (2020) ‘Keratoconus screening based on deep learning approach of corneal topography’, Translational Vision Science and Technology, 9(2), pp. 1–11. doi: 10.1167/tvst.9.2.53.

Lavric, A. et al. (2021) ‘Keratoconus Severity Detection from Elevation, Topography and Pachymetry Raw Data Using a Machine Learning Approach’, IEEE Access, 9, pp. 84344–84355. doi: 10.1109/ACCESS.2021.3086021.

Lin, S. R. et al. (2019) ‘A Review of Machine Learning Techniques for Keratoconus Detection and Refractive Surgery Screening’, Seminars in Ophthalmology, 34(4), pp. 317–326. doi: 10.1080/08820538.2019.1620812.

Liu, N. and Wang, H. (2006) ‘Recognition with Weighted Kernel Component Analysis’, Electronic Engineering, 00(6).

Mohammed, H., Kareem, S., & Mohammed, A. (2022). A COMPARATIVE EVALUATION OF DEEP LEARNING METHODS IN DIGITAL IMAGE CLASSIFICATION. Kufa Journal of Engineering, 13(4), 53-69.

P, S. and G P, R. (2022) ‘Keratoconus Classification with Convolutional Neural Networks Using Segmentation and Index Quantification of Eye Topography Images by Particle Swarm Optimisation’, BioMed research international, 2022, p. 8119685. doi: 10.1155/2022/8119685.

Piñero, D. P. (2016) ‘Corneal Topography from Theory to Practice (2013). Eds: Aylin Kiliç and Cynthia J. Roberts. Kugler Publications. ISBN: 978-90-6299-230-0’, Graefe’s Archive for Clinical and Experimental Ophthalmology, 254(10), pp. 2077–2078. doi: 10.1007/s00417-015-2942-1.

Qi, Y. et al. (2022) 'A Comprehensive Overview of Image Enhancement Techniques', Archives of Computational Methods in Engineering, 29(1), pp. 583–607. doi: 10.1007/s11831-021-09587-6.

Ren, X. D. et al. (2017) 'Convolutional neural network based on principal component analysis initialization for image classification', Proceedings - 2016 IEEE 1st International Conference on Data Science in Cyberspace, DSC 2016, pp. 329–334. doi: 10.1109/DSC.2016.18.

Saponara, S. and Elhanashi, A. (2022) 'Impact of Image Resizing on Deep Learning Detectors for Training Time and Model Performance', Lecture Notes in Electrical Engineering, 866 LNEE(January), pp. 10–17. doi: 10.1007/978-3-030-95498-7_2.

Schatteburg, J. and Langenbucher, A. (2022) 'Protocol for the diagnosis of keratoconus using convolutional neural networks', PLoS ONE, 17(2 February), pp. 1–10. doi: 10.1371/journal.pone.0264219.

Turk, M., & Pentland, A. (2015). E igedces for Recognition. Journal of Cognitive Neuroscience, 3(1).