International Journal of Computer Engineering and Data Science (ISSN: 2737-8543)
Volume 4–Issue 2, April - June 2025

Keratoconus Classification Using Multimodal Imaging Strategy

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Article history

Received Mar 15, 2025
Revised Jun 20, 2025
Accepted Jun 28, 2025
Published Jun 30, 2025

ABSTRACT

Abstract: Data fusion improves the accuracy and robustness of diagnostic models by combining different types of information. This study presents a multimodal framework for keratoconus classification. It uses numeric and textual features from Pentacam reports, extracted with OCR. These are combined with corneal topographic images processed by a dual-branch deep neural network. The method was tested on 2,924 labeled Pentacam scans. Of these, 1,900 were used for training and 1,024 for testing. Scans were labeled as normal, suspicious, or keratoconus. Results show that combining image and text features improves classification. Deep learning accuracy rose from 96.78% to 98.34%. SVM improved from 93.35% to 95.60%. LDA increased from 92.85% to 94.80%, and KNN from 90.50% to 93.94%. These gains, up to 1.56% for deep learning and 3.44% for KNN, show the value of multimodal data for more accurate keratoconus diagnosis.

Keywords: *Keratoconus Classification, Mumtimodal data fusion, Corneal topography, Machine learning, Deep Learning.*

I. INTRODUCTION

Currently, the diagnosis of keratoconus is essentially based on clinical examination and corneal imaging. Corneal imaging techniques, such as Schimpf photography and optical coherence tomography (OCT), can provide detailed information about the cornea and aid in the diagnosis of keratoconus [1]. However, interpretation of corneal images can be subjective and time-consuming.

With the growing popularity of machine learning (ML) and its accompanying implementations, there are increasing calls to create deployable and relevant decision support tools for the detection and classification of multiple diseases, including keratoconus.

Exploring how decisions are made by humans, they rarely rely on a single data point or source of information. This diversity of information sources gives rise to information fusion in the context of multimodal machine learning [2]. For example, a clinical diagnosis made by a physician is typically based on a constellation of lab results, signs and symptoms, and imaging that, when contextualized together, lead to a decision/classification.

Data fusion is a technique of combining data from different sources to create analytical data sets that can be used to make more precise decisions addressing specific issues by applying in-depth analysis [3]. Data fusion allows various types of data from different sources to be integrated into an analysis, which helps obtain higher quality, actionable insights for the analysis process [4]. Merging two or more datasets often reveals relevant features that could not have been discovered when using each dataset separately [5]. These revealed characteristics can offer new insights, leading to more informed decisions.

Three different categories of data fusion can be distinguished, each depending on the processing step at which the data fusion occurs:

Low-level fusion: Combines multiple raw data sources directly to produce new, more informative raw data [6].

Mid-level fusion: Features are first extracted from input data before being fused. These can include variables, latent features, shapes, or positions in images [6].

High-level fusion: Supervised models are applied to each dataset individually. The decisions of these models are then combined to improve prediction or classification accuracy [6].

Although corneal imaging provides detailed data, its interpretation remains subjective and time-consuming, which may lead to diagnostic variability [7]. There is a need for automated, objective, and accurate methods for the diagnosis of keratoconus that can support clinicians and improve diagnostic efficiency.

Additionally, existing automated methods often rely on a single data source, which may not capture the full complexity of the disease. A multi-source approach using data fusion can reveal hidden patterns and improve classification performance.

In this work, we propose a deep learning approach for keratoconus classification using mid-level feature fusion. The proposed method combines several features extracted from corneal topographic images to improve the accuracy of keratoconus classification.

The approach is evaluated on a dataset composed of 2924 corneal topographic images and demonstrates promising results. It paves the way for the development of automated keratoconus detection systems that can aid in the early diagnosis and effective management of the disease.

The remainder of this paper is organized as follows: Section 2 persents related works on data fusion in keratoconus classification. Section 3 describes the adopted methodology of keratoconus classification. Section 4 reports and discusses the obtained results. Section 5 provides conclusions of the proposed approach.

II. Related Works

Various machine learning techniques have been used in the diagnosis and classification of diseases, including keratoconus. Data fusion is one of the most widely used ML techniques in the literature.

The authors of [8] proposed the LKG-Net system for the classification of keratoconus according to the 4 levels Normal, Mild, Moderate and Severe using data fusion. This system is based on a multi-level feature fusion module to merge data from upper and lower levels to obtain more abundant and efficient features. Evaluated on a total of 488 topographic images from 281 people, this model achieved 89.55% for weighted recall, 89.98% for weighted precision and 89.50% for weighted F1-score respectively.

In the study [9], the authors developed a system based on the Xception and InceptionResNetV2 architectures to extract features from three different corneal maps collected from 1371 eyes examined at an eye clinic in Egypt. These features were fused using Xception and InceptionResNetV2 to detect subclinical forms of keratoconus more accurately and robustly. The proposed system achieved an AUC of 0.99 and an accuracy range of 97% to 100% in distinguishing normal eyes from eyes with subclinical keratoconus.

The authors of [10] proposed the KerNet system for detecting keratoconus and subclinical keratoconus based on the raw data of the Pentacam HR system. This system is based on the fusion of five digital matrices, corresponding to the curvature of the front and rear surfaces, the elevation of the front and rear surfaces and the pachymetry of an eye. The results generated by this system achieved an accuracy of 94.74%, a recall of 93.71%, a precision of 94.10% and an F1-score of around 93.89%.

The keratoconus detection system proposed in [11] is based on the use of a camera of a smart device to capture photographed eye images of the anterior and lateral segments. Using a set of 280 images, the corneal area of the images was segmented in order to extract geometric features. The results obtained by this system showed that the fusion of all features was able to generate an accuracy of 96.05%, a sensitivity of 98.41% and a specificity of 93.65% with the Random Forest classifier.

The authors of [12] proposed a system for identifying the base curve in rigid gas permeable (RGP) lenses based on supervised image processing and classification of the four Pentacam refractive maps in the case of irregular astigmatism. Using a dataset of 247 four labeled Pentacam refractive maps, two novel feature extraction techniques, namely quantization-based radial-sector segmentation (QRSS) and deep convolutional neural networks, were used to extract the different characteristics. Feature fusion was applied and the RGP base curve was identified by the regression layer of a neural network. The results achieved a coefficient of determination of 0.9642 and a root mean square error of 0.0089.

III. Methodology

The proposed keratoconus classification method is based on the analysis of topographic images of patients. These corneal topographic images are composed of four topographic maps, namely corneal thickness, elevation back, elevation front and sagittal curvature. In addition to these maps, the images include annotations, measurements and text representing certain corneal characteristics.

The idea of the proposed approach is based on extracting the textual values contained in the different corneal topographic images and saving them in separate text files before cleaning these original images. The second step consists of combining the extracted values and the cleaned images during the classification phase in order to improve the predictive performance of the different classifiers used in this study.

Thus, the proposed architecture consists of two branches: the first branch is dedicated to extracting the textual features included in the images, and the second branch focuses on extracting the features from the cleaned images. An overview of the different steps of the adopted methodology is illustrated in Figure 1.

International Journal of Computer Engineering and Data Science (ISSN: 2737-8543)
Volume 4–Issue 2, April - June 2025

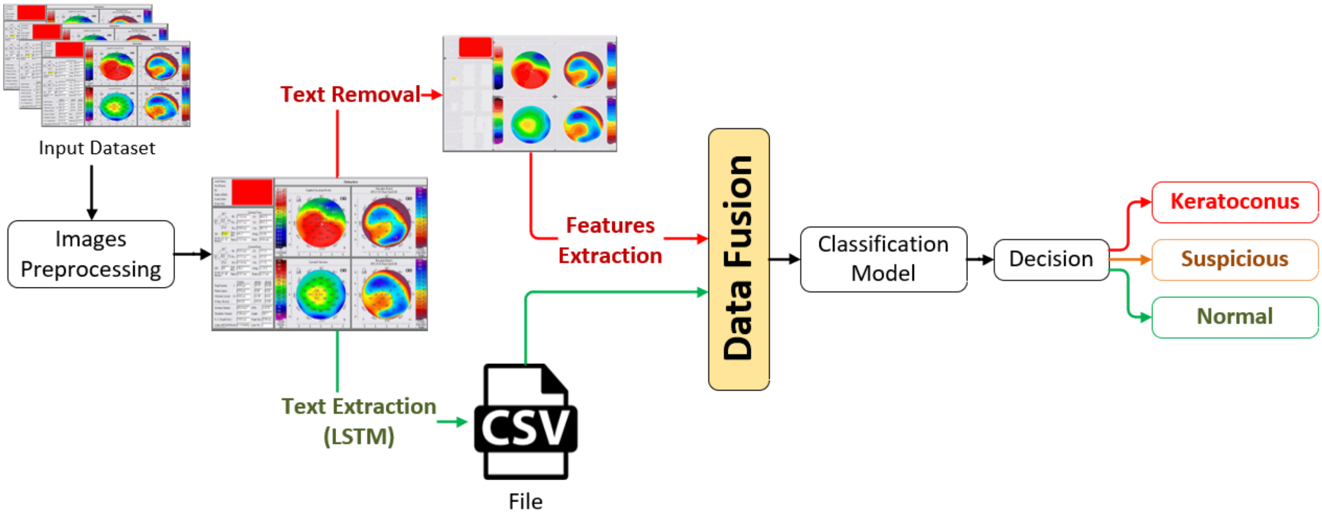
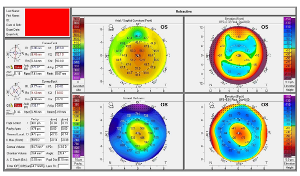


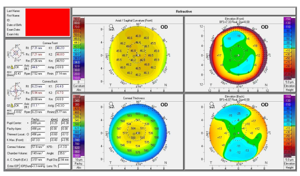
Figure 1: Adopted data fusion approach.

A. Data collection

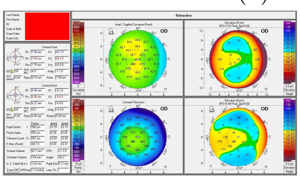
The dataset used in this study is composed of a total of 2924 images captured, anonymously, using a Pentacam device [13]. Each corneal topographic image represents the cornea of a different patient. The retained part of these images consists of the four maps (corneal thickness, sagittal curvature, rear and front elevations) in 1024x729 JPEG format as shown in the figure 2. The captured images were classified and labeled manually, by specialists, considering three corneal classes, which are : normal, suspicious and keratoconus corneal classes.



(a) Keratoconus.



(b) Normal.



(c) Suspicious.

Figure 2: Topographies of the different corneal classes.

B. Proposed approach

1. Data preprocessing

The data preprocessing step for diseases classification, including keratoconus, is very essential to ensure better accuracy of the model. Thus, corneal topographic images were preprocessed to correct distortions and to eliminate image noise from the entire data set. As shown in figure 2, topographic images contain, in addition to the topography of the corneas, digital measurements and textual annotations.

Before proceeding with the classification of keratoconus, the next step is then to retrieve these textual measurements from the images and save them in .CSV files separately before excluding them from the images.

2. Textual features extraction

For text extraction, the adopted technique is based on optical character recognition (OCR) tool using python [14]. This tool allows reading plain text and tables from image and PDF files using an OCR engine and provides intelligent post-processing options to ensure results in the desired formats.

The textual features extraction branch used in this study is composed of the following layers, as illustrated in Figure 3:

- **An Embedding layer** : This embedding layer can be seen as transforming data from a higher dimensional space to a lower dimensional space, or it can be seen as a mapping of data from a space from lower dimension to higher dimensional space;
- **An LSTM layer** : with 100 units, this layer essentially implements an LSTM type recurrent model, which is one of the variants of recurrent neural networks;
- **A dense layer** : (text_features) with 100 units;
- **A ReLU activation function**.

The extracted text values for each corneal class were stored in a separate .CSV file. Thus, three resulting csv files were created, namely suspicious.csv, normal.csv and keratoconus.csv. To ensure better classification performance and improve the robustness of the model, images of poor quality were removed.

3. Text Removal

Figure 4 (a) represents an original corneal topography, including annotations and text values. Once the text values have been extracted from the images and saved separately, these images will be cleaned. For this purpose, these images were subjected in the next step to a process of eliminating these annotations by following a particular treatment detailed in the following section.

In order to exclude text that is potentially harmful to the learning process, these corneal topography images must be subjected to inpainting techniques and algorithms to be able to repair and restore them. Thus, the OpenCV tool was used for this purpose [15], the images are downloaded and then converted to grayscale, subsequently a rectangular kernel of (6x6) is built and a blackhat operation that allows finding dark regions on a light background is applied to these images to detect the textual values existing on the images. This process is illustrated in Figure 4.

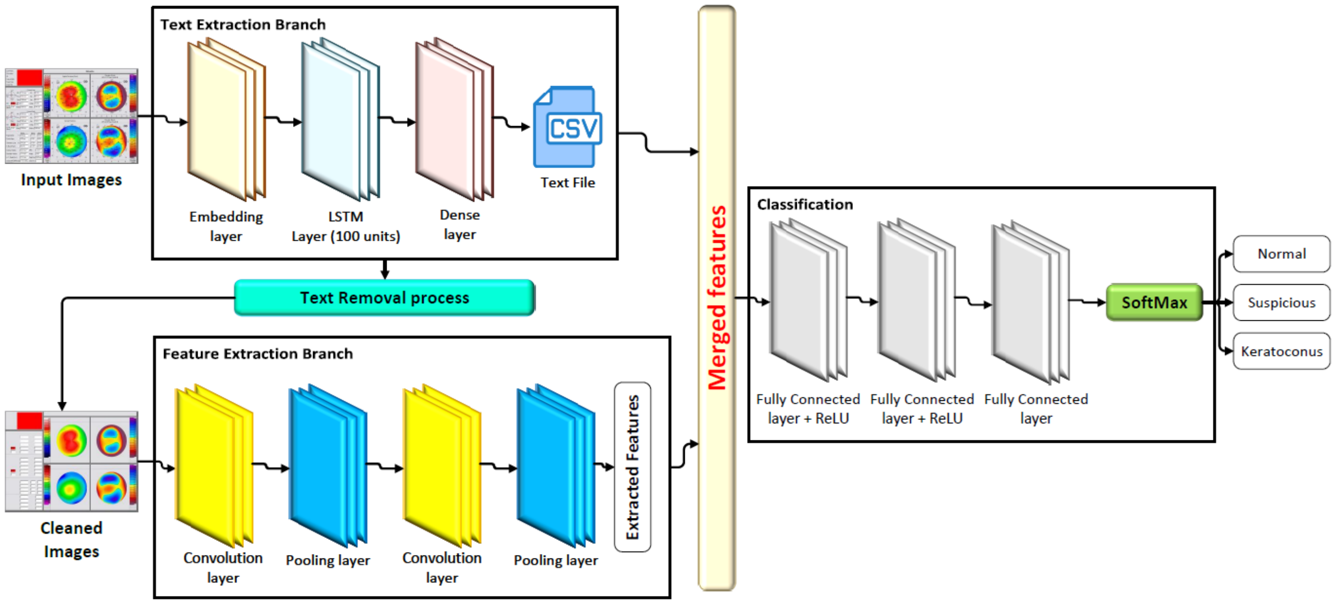


Figure 3: Text and features extraction process.

The images resulting from this step are subsequently subjected to binary thresholding with a threshold of 10. Thus, all pixel values above the specified threshold 10 are set to a maximum value of 255 and all pixel values below 10 are set to 0.

The mask image indicates where the damage to exclude is located in the image. This image must have the same spatial dimensions (width and height) as the input image. Non-zero pixels correspond to areas that need to be painted (i.e. fixed), while zero pixels are considered normal and do not need to be painted. Figure 4 (b) below shows a mask image of the original image 4 (a).

Subsequently, the image inpainting technique based on Telea's fast walking method is applied [16], using the original images and the previously thresholded images as the inpainting mask. The return image is a restored image without text, as shown in the figure 4 (c), representing an example of a topographic image after extraction and elimination of text values. This process is applied to all images in the dataset.

Thus, the inputs of the future keratoconus classification model will be of two types: cleaned corneal topographic image data and textual data previously extracted from these same images before eliminating them.

4. Features extraction from cleaned images

As indicated in Figure 3, the cleaned-image feature extraction branch starts with a convolutional layer (conv1_1) that has 32 filters with a kernel size of 3x3, followed by a ReLU activation. The output is then passed to a max-pooling layer (pool1_1) with a pool size of 2x2. This process is repeated with another convolutional layer (conv1_2) with 64 filters and a ReLU activation, followed by another max-pooling layer (pool1_2) with a pool size of 2x2. The output of this branch is then flattened.

The output of this branch is then merged with the result of the text extraction branch from images. Indeed,

International Journal of Computer Engineering and Data Science (ISSN: 2737-8543)
Volume 4–Issue 2, April - June 2025

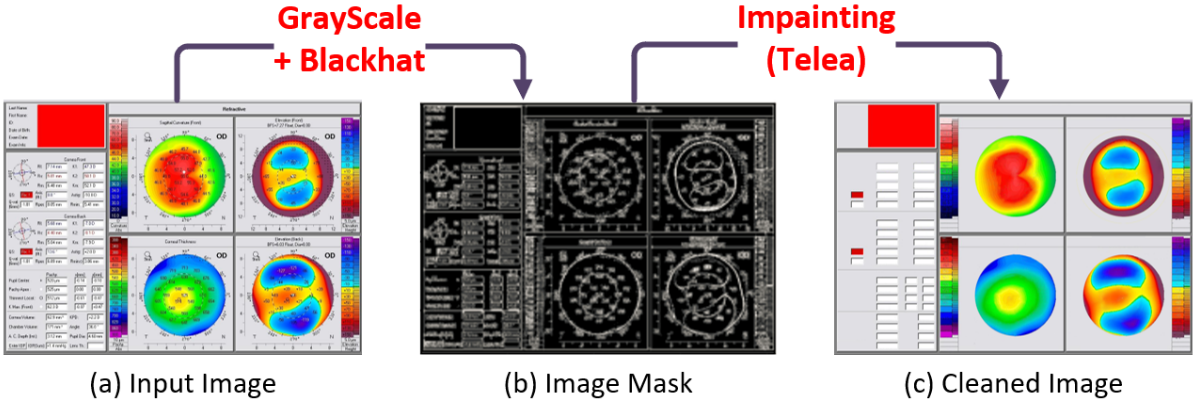


Figure 4: Text removal process.

these two branches are then merged by concatenating the image features and the text features (merged_features). The output is then passed through two fully connected layers with 128 and 64 units respectively and a ReLU activation. The final output is a dense layer with 3 units and a softmax activation.

5. *Data fusion (Images et text)*

Feature fusion refers to the process of combining information from multiple sources, images and text, to improve the predictive performance of the learning model used for keratoconus classification. This could involve combining information from multiple modalities, such as combining information about the shape of the cornea and the size of certain features, or combining information from multiple layers of the deep learning model. By combining information from multiple sources, the model is able to make more accurate predictions and improve its classification accuracy.

In this study, the classification of keratoconus consists of combining data from two different formats, images and text data, to obtain more accurate results using mid-level fusion technique.

6. *Classification model*

Once the textual data and the corneal topographic image data were extracted and merged, by concatenating these data, the resulting dataset was used as input for the models responsible for classifying corneas into three different classes (normal, suspicious and keratoconus). Four different models were adopted for the classification of keratoconus, these models were tested on the data before and after data fusion. These models are :

- Support Vector Machine (SVM);
- Linear Discriminant Analysis (LDA);
- K-Nearest Neighbors (KNN).
- A Deep learning (DL) model: This classification model consists of three different dense layers. The first fully connected layer with a total of 128 units and a ReLU activation function. The second dense layer is composed with 64 units and a ReLU activation function. The final classification of corneas is ensured by the third fully connected layer with 3 units and a Softmax activation function. To avoid the overfitting problem when training the adopted DL model, a Dropout of 0.2 is applied in order to ignore 20% of the nodes of the layers at random during training.

For the training and validation of the model used, the data are sent as and when. Indeed, a data normalization has been applied and uniform batches of a size of 32 elements are used for loading the data. This allows to process image data with normalized values between 0 and 1, and no longer on their entire RGB color scales, which extends from 0 to 255, which allows a better understanding of the classification model used for the discrimination of keratoconus.

For the different machine learning models SVM, LDA and KNN, the 10-fold cross-validation technique was used to avoid the overfitting problem.

7. *Evaluation Metrics*

To evaluate the classification performances of the models adopted in this study in an objective and complete manner, the evaluation metrics used are:

- Accuracy;
- Precision;
- Recall;
- F1-score;
- Confusion matrix.

International Journal of Computer Engineering and Data Science (ISSN: 2737-8543)
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These metrics are used to examine the ability of the adopted models to more precisely and accurately predict the different classes of patients' corneal topographic images.

IV. RESULTS

A. Dataset

The initial dataset used in this study consists of corneal topographic images in JPEG format, with a total of 2924 images representing the three corneal classes normal, suspicious and keratoconus. Table 1 details the dataset used in this study.

Table 1: Description of training and testing data.

Classes	**Training**	**Test**
keratoconus	221	120
Normal	1102	593
Suspicious	577	311
Total of Images	1900	1024
Percentage	65%	35%

After the quality control step, the dataset was divided into two subsets. A training subset consisting of 65% of the corneal images (i.e. 1900 images). The second subset is the validation subset, consisting of 35% of the corneal images (i.e. 1024 images).

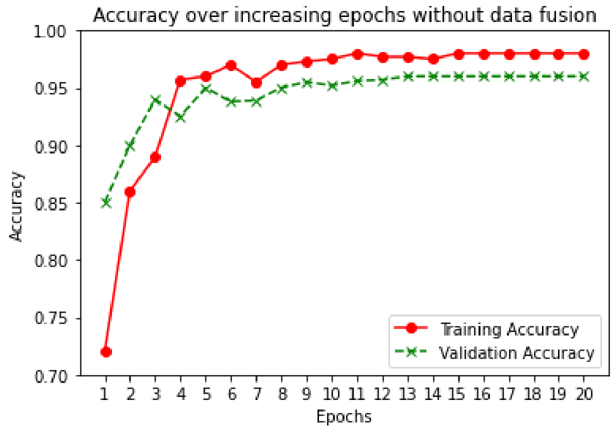
B. Experimental Setup

The simulation results are obtained using a computer equipped with an Intel(R) Core(TM) i5-6300U CPU @ 2.40GHz 2.40GHz, a RAM of 8.00 GB, the Windows 10 Professional operating system, tensorflow and the keras library in Python 3.7.4 on Jupyter notebooks.

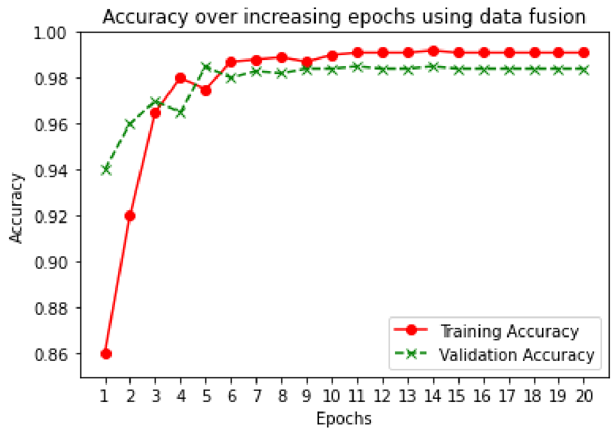
C. Experimental Results

To train and validate the adopted CNN model on the training and validation sets, the optimizer used is Adam with a learning rate of 0.001. Training was performed using batches of uniformly sized images of 32 elements over 20 epochs.

Figure 5 (a) illustrates the evolution curve of the classification accuracy using DL model before applying data fusion. Figure 5 (b) indicates the evolution curve of the classification accuracy using DL model after applying data fusion.



(a) Classification before data fusion using DL model.



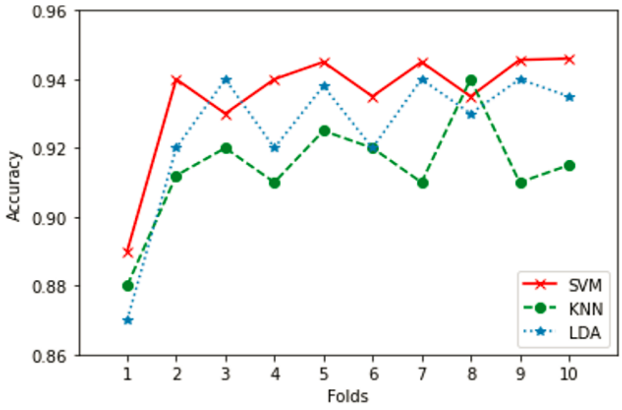
(b) Classification after data fusion using DL model.

Figure 5: Performance of DL model.

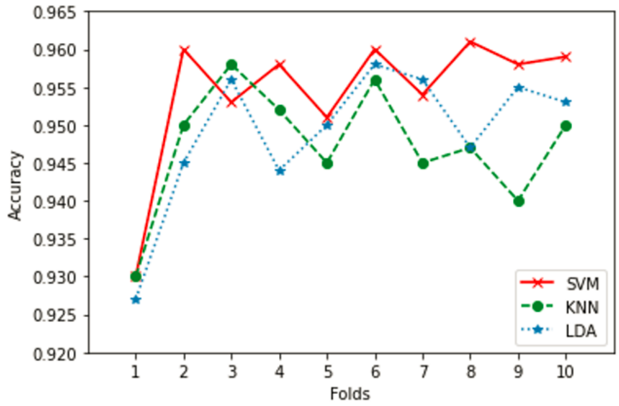
After the first step of keratoconus classification, which consists of using the adopted DL model, the second step of classification consists of classification using three different ML models, namely: Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and k-Nearest Neighbors (KNN).

Figure 6 shows the classification performances by the different ML models (i.e. SVM, LDA and KNN) used for the classification of keratoconus before fusion (A), then after fusion (B) of the data. It should be recalled that a 10-fold cross-validation was used for the different models in order to avoid over-fitting problems.

Figures 5 and 6 clearly indicate that the predictive performance of the adopted DL and ML models have been significantly improved by using the data fusion technique. Indeed, concatenating the textual data extracted from the topographic images with the original images has resulted in good performance compared to the results obtained by using only the images during classification.



(a) Classification before data fusion using ML models.



(b) Classification after data fusion using ML models.

Figure 6: Performance of ML models.

V. Discussion

The aim of using the data fusion technique in this study is to improve the accuracy of keratoconus classification by combining the data representing the topographic images and the textual annotations and metrics present on these images. Thus, the metrics and textual annotations present on the different images were retrieved and saved in separate files, then combined with the cleaned images for a more accurate classification of corneas.

As shown in the Table 2, the deep learning model, when applied without fusion, already achieved relatively high classification accuracy across all classes. However, the introduction of data fusion, combining both textual features and corneal topographic images, led to significant improvements in classification performance.

More specifically, the accuracy for the keratoconus class increased from 97.56% to 98.93%, which is particularly noteworthy as this class represents the primary clinical concern in the early detection and management of the disease. The precision and recall for keratoconus also improved substantially, indicating that the model not only correctly identifies more true positives but also reduces false negatives.

The Normal and Suspicious classes also benefited from the fusion process, achieving near-perfect recall and precision. The suspicious cases, which often represent borderline or ambiguous conditions, showed an increase in classification accuracy from 97.66% to 98.44%, suggesting that the additional textual data provided complementary information that enhanced the model's discriminatory power.

The overall classification accuracy increased from 96.78% to 98.34%, confirming that the proposed data fusion strategy significantly enhances the predictive performance of the adopted deep learning model.

Table 2: Classification performanc of adopted DL model.

Technique	Class	Precision	Recall	F1-score	Accuracy
Without Fusion	Keratoconus	92.00%	87.00%	89.00%	97.56%
	Normal	98.00%	99.00%	99.00%	98.34%
	Suspicious	96.00%	96.00%	96.00%	97.66%
	Global Classification Accuracy				**96.78%**
With Fusion	Keratoconus	97.00%	94.00%	95.00%	98.93%
	Normal	99.00%	100.0%	99.00%	99.32%
	Suspicious	98.00%	97.00%	97.00%	98.44%
	Global Classification Accuracy				**98.34%**

Table 3 presents a comparative analysis of the classification performance of machine learning models (SVM, LDA, and KNN) for keratoconus detection, both without and with the application of the data fusion technique.

Without data fusion, the Support Vector Machine (SVM) model achieved the highest classification accuracy of 93.35%, followed by Linear Discriminant Analysis (LDA) with an accuracy of 92.85% and K-Nearest Neighbors (KNN) with 90.50%. Although these results demonstrate reasonable classification capabilities, the models' performances were limited by the use of a single data modality, relying solely on corneal topographic images.

With the introduction of data fusion, significant performance improvements were observed across all models. The accuracy of SVM increased to 95.60%, LDA to 94.80%, and KNN to 93.94%. Precision, recall, and F1-score also improved consistently, confirming the positive impact of combining multimodal data on the models' discriminative abilities.

Among the models, SVM consistently achieved the best performance, both before and after data fusion, suggesting that SVM is particularly effective for this classification task given the nature of the feature space.

Table 3: Classification performance of SVM, LDA et KNN models.

Technique	Model	Precision	Recall	F1-score	Accuracy
Without Data Fusion	SVM	93.00%	93.00%	93.00%	**93.35%**
	LDA	92.00%	93.00%	92.00%	92.85%
	KNN	90.00%	91.00%	89.50%	90.50%
With Data Fusion	SVM	96.00%	95.90%	96.00%	**95.60%**
	LDA	95.00%	94.00%	95.00%	94.80%
	KNN	93.00%	94.00%	94.00%	93.94%

The analysis of obtained results confirm that multimodal data fusion enhances the performance of classical machine learning models in keratoconus classification. These findings align with existing literature and reinforce the importance of integrating diverse data sources in medical image analysis to improve diagnostic accuracy and reliability.

VI. CONCLUSION

This study demonstrates that fusing numeric and textual data from Pentacam reports with corneal topography images significantly enhances the accuracy of keratoconus classification. The proposed two-branch deep learning network successfully integrates these multimodal data sources, leading to measurable performance improvements across all tested classification models. Specifically, accuracy increased from 96.78% to 98.34% for deep learning, from 93.35% to 95.60% for SVM, from 92.85% to 94.80% for LDA, and from 90.50% to 93.94% for KNN.

These results not only support our initial hypothesis but are also consistent with previous research suggesting that multimodal data fusion improves diagnostic accuracy in medical classification tasks. The findings align with and reinforce existing theories in the field of medical artificial intelligence, particularly those related to the added value of integrating diverse sources of information. Overall, the study contributes to the development of more effective AI-based decision support tools in ophthalmology.

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