RESEARCH PAPER

Multi-Map Attention Ensemble Network (MMAEN) for Automated Keratoconus Detection using Corneal Topography Images: A Deep Learning Approach with Cross-Map Attention Mechanism

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Abstract: Keratoconus is a corneal progressive disorder, and if it is not detected earlier, can also lead to visual impairment. There are numerous traditional diagnosis techniques of corneal topography, which helps interpret the KC at clinical level. Therefore, if we are doing early-stage keratoconus detection, there may be a little difference in accuracies. In this study, we have proposed a novel model which includes multi-map attention ensemble network (MMAEN). Here we are using multiple corneal topographic maps and cross-map attention mechanism which helps for automated detection of keratoconus. MMAEN includes seven parallel EfficientNet-B0 feature extractors, where they process corneal maps 224x224x3 pixels. These features are integrated using cross-map attention mechanism, where the features of these maps also have optimal weighting. In this architecture, 5.27 million parameters are present, and we have used uncertainty quantification, and we have used Monte Carlo dropout method for uncertainty quantification. The evaluation of this model includes experimental configuration, that is original corneal topography images and pre-processed images, which includes ImageJ software. The pre-processed image configuration has achieved 97% test accuracy with 94% keratoconus sensitivity and 100% normal specificity. The original image configuration has achieved 94% accuracy and 88% sensitivity, which achieved 3% accuracy improvement with false negative, with 50% decrease in the false negative. In these two configurations, AUC score is very high for original it is 0.996 and for pre-processed it is 0.992. As well, we have calculated Cohen's kappa values 0.880 and 0.940 respectively, and that is why the reliability of model is achieved. MMAEN is an innovative multi-map attention framework, that is used for the automated keratoconus detection which gives superior performance. The pre-processing on the images eventually reduces false negatives, which gives early disease detection at the clinical level. This advance model also includes uncertainty quantification, which gives confidence estimates while predictions, also improves the clinical utility.

Keywords: Keratoconus detection, Corneal Topography, Deep Learning, Attention Mechanism, Multi-map Fusion, computer-aided diagnosis, EfficientNet, Ophthalmology, Medical Image Analysis.

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1. Introduction

Keratoconus is a corneal non-inflammatory and progressive disorder. In this, the corneal layers progressively thin out that leads to protrusion of the cornea part of eye, which results in irregular astigmatism as well as visual impairment [8]. This condition basically happens during adolescence and early adulthood, with the prevalence estimated from 50 to 230 per one lakh individuals globally [2]. The detection of the keratoconus at early-stage is really important because corneal cross-linking can also halt the disease progression and then prevent the need of corneal transplantation in the advanced cases [3]. The traditional keratoconus diagnosis basically relies on the clinical examination that are combined with corneal topography map analysis, where the ophthalmologists interpret the color-coded maps which describes different corneal parameters that includes attributes such as axial curvature, elevation, pachymetry, and refractive power. However, this diagnostic strategy even faces some challenges. At First, early-stage or subclinical keratoconus shows some subtle topographic changes that may be difficult to differentiate from normal corneal variations, that leads to delayed diagnosis of the Keratoconus [8,15]. Second, the keratoconus diagnostic accuracy basically depends on the clinician expertise as well as experiences of clinicians, that introduces the subjectivity and interobserver variability [5]. Third, the increasing adaptability of the keratoconus screening system examinations in clinical practice produces workflow bottlenecks, mainly in resource-limited settings [1]. The origin of deep learning technique has transformed the medical image analysis, with the advanced convolutional neural networks (CNNs) that demonstrates the remarkable success in the automated disease detection over different ophthalmological conditions [9,19]. Earlier literature research studies have explored advanced deep learning strategies for keratoconus detection, that employs pre-trained architectures such as ResNet, VGG, and EfficientNet on corneal topography images[2,8,6]. These literature studies have circulated promising results, with high accuracies that ranges from 88% to 99% depending on the dataset characteristics and model frameworks [7]. Even these advances, that existing approaches faces some limitations. Recent studies use single corneal maps as well as simple concatenation of multiple maps, that fails capturing the complex inter-relationships between distinct topographic parameters [3]. Also, there are many models lack uncertainty quantification mechanisms, that are important for clinical deployment where the prediction confidence directly impacts on clinical decision-making [10]. Furthermore, the limited attention has been given to systematic preprocessing approaches that could enhance the model performance by improving the image quality and reducing the noise in corneal topography data.

Addressing such gaps, we presented the Multi-Map Attention Ensemble Network (MMAEN), a novel deep learning framework specifically designed for automated keratoconus detection using corneal topography images. MMAEN model introduces three key innovations: (1) the parallel processing of seven different corneal maps through the committed EfficientNet-B0 feature extractors, (2) a cross-map attention mechanism which also learns optimal feature weighting over distinct topographic parameters, and (3) also integrated Monte Carlo dropout for uncertainty quantification. We evaluated the MMAEN model on two experimental configurations i.e. original and pre-processed images to assess the impact of systematic pre-processing on diagnostic performance[20].

2. Literature Review

The application of deep learning detection of keratoconus has achieved substantial momentum since 2020, with the researchers exploring various CNN architectures, image input modalities, and training strategies[17,18]. This section provides a comprehensive review of recent advances in the automated keratoconus detection, organized by methodology, dataset characteristics, and performance outcomes.

There are recent studies that have explored deep learning architectures for the detection of the keratoconus using corneal map imaging. Pre-trained transfer learning models such as VGG16, ResNet, Efficient Net, and Xception have illustrated high diagnostic performance, which achieved accuracy and AUC values above 0.95 in some cases [2,8,3]. The Feature fusion techniques that concatenate multiple corneal maps, including sagittal map, elevation maps, and pachymetry maps, have additional improved generalization over the datasets. Additionally, the visualization techniques, like heatmaps, have also enhanced clinical interpretability. The recent work has focused on specialized systems such as automated feature selection [6], the early-stage keratoconus detection [7], and disease progression analysis [5]. Novel frameworks like Feature Vector Aggregation Networks as well as deep feature fusion models [4] highlights the recent trend towards the advanced technology of integrating multi-level features for highly improved accuracy [13,14,]. Even though, there are many research studies that are limited by small or retrospective research datasets, lack of multi-ethnic validation, and insufficient reporting of the dataset characteristics and performance metrics, that indicates the need for more robust and generalized architectures.

3. Methodology

3.1 MMAEN Architecture

The Multi-Map Attention Ensemble Network (MMAEN) is designed to influence complementary information from the corneal topography maps through a sophisticated attention-based fusion mechanism. Figure 1 shows the complete framework of MMAEN.

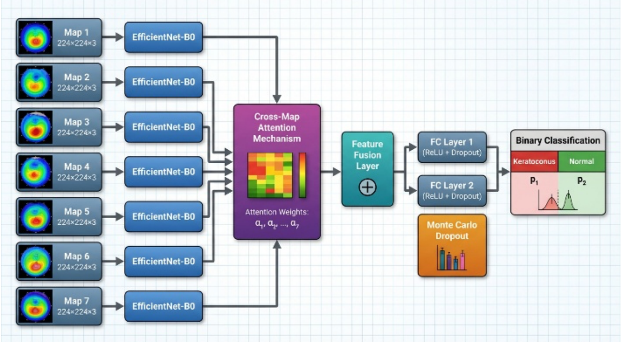


Figure 1: MMAEN Architecture for Automated Keratoconus Detection

The architecture shows 7 parallel corneal map inputs (224×224×3 pixels each) that are processed using EfficientNet-B0 feature extractors, and then integrated via cross-map attention mechanism, followed by feature fusion layer and fully connected layers with Monte Carlo dropout for the binary classification with uncertainty quantification.

3.1.1. Multi-Map Input Processing

MMAEN processes seven distinct corneal topography maps simultaneously, each representing different corneal parameters. Each map is standardized to 224×224×3-pixel resolution, maintaining the color-coded representation that encodes quantitative corneal parameters through a standardized colour scale. This multi-map approach ensures comprehensive capture of keratoconus-related corneal changes across different measurement modalities. The dataset is available online, with reference to [4] research study.

3.1.2 Parallel Feature Extraction with EfficientNet-B0

Each of the seven corneal maps is processed through a dedicated EfficientNet-B0 backbone network. EfficientNet-B0 was selected for several reasons such as Efficiency, EfficientNet-B0 achieves state-of-the-art accuracy withcomparatively fewer parameters (5.3M) as compared to other models like ResNet50 (25.6M) or VGG16 (138M), allowing faster training and inference [2].Compound Scaling, EfficientNet shows compound scaling which uniformly scales the network depth, width, and resolution, that optimizes the balance between model accuracy and computational efficacy. Transfer Learning, Pre-trained networks on ImageNet, EfficientNet-B0 gives robust low-level feature extraction capabilities which helps transfer productively to medical imaging domains [3]. Each EfficientNet-B0 model backbone extracts total 1280-dimensional feature vector from its respective corneal map(multiple), that results in seven feature vectors which capture map-specific corneal attributes. The parallel framework ensures that each map's unique information is stored during initial feature extraction before the fusion of features.

3.1.3 Cross-Map Attention Mechanism

The core innovation of MMAEN is the cross-map attention mechanism, which learns to dynamically weight features from different corneal maps based on their relevance for keratoconus detection. The attention mechanism operates as follows:

Attention Weight Computation: For each map i (where i = 1, 2, ..., 7), the attention mechanism computes/calculates an attention weight α_i that shows the importance of that map's features for the current prediction:

$$\alpha i = \mathrm{softmax}(Wa \cdot fi + ba) \qquad (1)$$

where f_i is the feature vector from map i, as well as W_a is a learnable weight matrix, and b_a is a bias term. The softmax function ensures that attention weights sum to 1 across all maps.

Attention-Weighted Feature Fusion: The final fused feature vector F is computed as a weighted combination of individual map features:

$$F = \Sigma i{=}1[7]\ \alpha i \cdot fi \qquad (2)$$

This attention-based fusion allows the model to adaptively emphasize maps that contain the most discriminative information for each specific case, rather than treating all maps equally. For example, in early-stage keratoconus, posterior elevation and pachymetry maps may receive higher attention weights due to their sensitivity to early changes, while in advanced cases, axial curvature maps may dominate [3,8,11,17]

3.1.4 Classification Head with Uncertainty Quantification

The attention-weighted fused features are passed through a classification head consisting of four Layers,

1. Feature Fusion Layer: A dense layer that further integrates the attention-weighted features, learning higher-level representations for classification.
2. Fully Connected Layers: Two fully connected layers (FC Layer 1 and FC Layer 2) with ReLU activation and dropout regularization. These layers

progressively transform the fused features into class-discriminative representations.

3. Monte Carlo Dropout: During both training and inference, dropout is applied with a rate of 0.3. At inference time, multiple forward passes (typically 20-50) are performed with different dropout masks, generating a distribution of predictions. This Monte Carlo dropout approach provides uncertainty quantification by measuring prediction variance across multiple stochastic forward passes [10].

4. Binary Classification Output: The final layer produces two outputs representing the probability of keratoconus and normal classes, with softmax activation ensuring probabilities sum to 1.

3.2 Dataset Description

3.2.1 Data Collection and Patient Demographics

The dataset contains corneal topography images acquired from patients undergoing routine ophthalmological examination and keratoconus screening. The dataset includes total 100 test cases (50 keratoconus, 50 normal) acquired using: Corneal topography imaging system capturing seven distinct map types, each map is standardized to 224×224×3 pixels, Standardized colour scale representing quantitative corneal parameters. Patient demographics and clinical characteristics were balanced between keratoconus and normal groups to minimize selection bias. All keratoconus cases were confirmed through comprehensive clinical examination including slit-lamp biomicroscopy, corneal topography analysis, and optical coherence tomography.

3.2.2 Data Preprocessing

Two experimental configurations were evaluated to assess the impact of preprocessing on model performance; one is original and other is pre-processed images. The image preprocessing is done using ImageJ software using removing outlier’s function[18]. The preprocessing pipeline was designed to enhance subtle topographic features characteristic of early-stage keratoconus while maintaining the quantitative relationships encoded in the color-coded maps.

Uncertainty Metrics:

Confidence: Mean predicted probability across Monte Carlo samples, indicating the model's certainty in its prediction.

Stability: Standard deviation of predictions across Monte Carlo samples, with lower values indicating more stable and reliable predictions.

3.3.3 Evaluation Metrics

Comprehensive evaluation metrics were calculated to assess the clinical utility. We evaluated using Primary Metrics such as Accuracy, Sensitivity (Recall), Specificity, Precision, F1-Score. Clinical Metrics such as False Negative Rate, False Positive Rate, Cohen's Kappa. Discrimination Metrics such as AUC-ROC, Confidence, Stability.

4. Results

4.1 Original Images Experiment

The MMAEN model trained on original corneal topography images achieved strong baseline performance across all evaluation metrics (Table 2).

Table 2: Performance Metrics for Original Images and Pre-processed Images Configuration

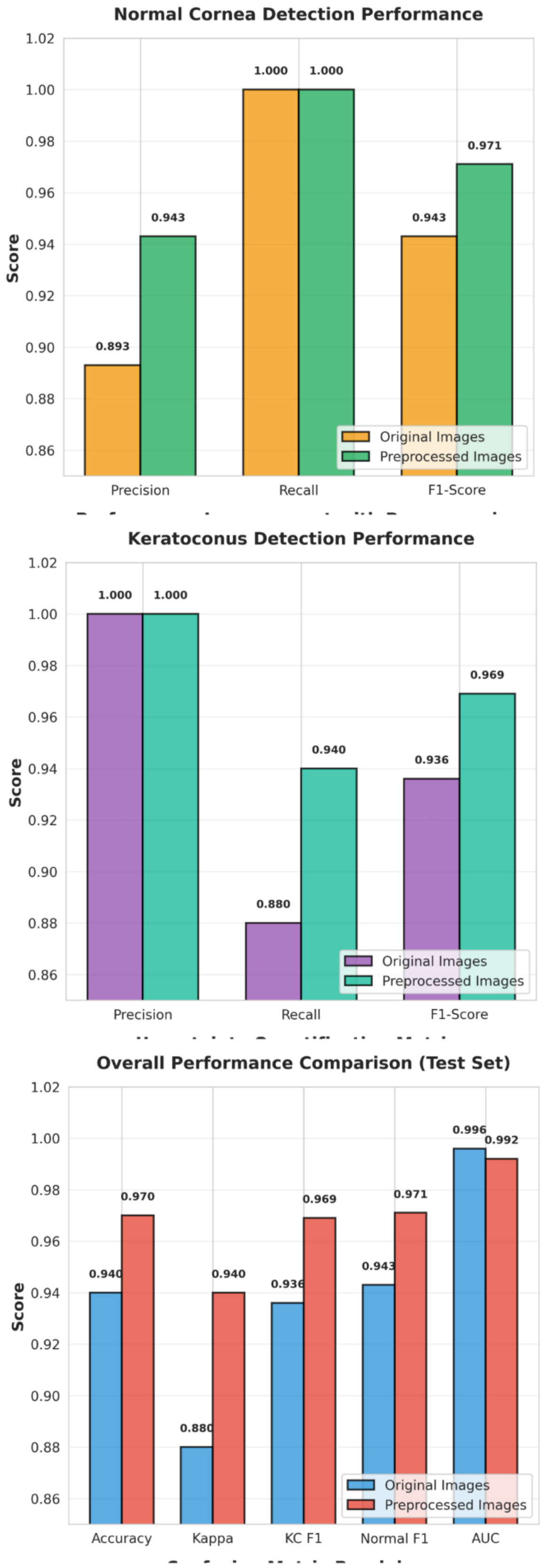
Metric	Value (Original)	Value (Pre-processed)
Test Accuracy	94.0%	97.0%
Keratoconus Sensitivity	88.0%	94.0%
Normal Specificity	100.0%	100.0%
Keratoconus Precision	100.0%	100.0%
Normal Precision	89.3%	94.3%
Keratoconus F1-Score	93.6%	96.9%
Normal F1-Score	94.3%	97.1%
Cohen's Kappa	0.880	0.940
Average AUC	0.996	0.992
False Negatives	6	3
False Positives	0	0
Confidence (Mean)	0.9598	0.9556
Stability (Std Dev)	0.9234	0.9218

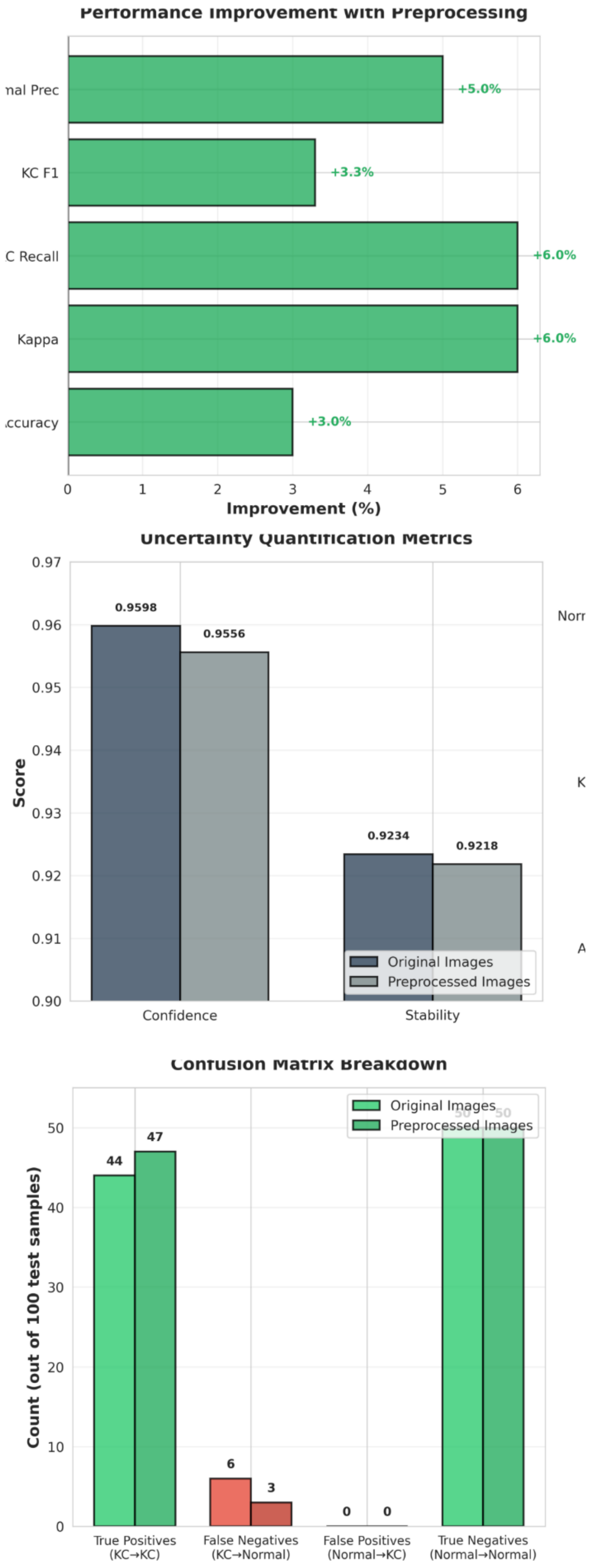
The original image configuration has achieved accuracy with 94% and 100% specificity and showed 88% sensitivity that results in 6 false negatives, that may cause delay in treatment. The model has achieved 97% test accuracy while evaluation of pre-processed images, with the increased sensitivity from 88% to 94%, which reduced the false negatives from 6 to 3 cases, that is 50% reduction in missed diagnosis. Such diagnosis improves clinical significance as it represents the false and as to prevent the false negatives which represents the correct diagnosis, the false negative is seen time to time diagnosis and treatment. While the average AUC decreased slightly from 0.996 to 0.992, this minimum difference is negligible and both the values shows excellent discrimination capability. Specificity survived perfect at the 100%, that maintains zero false positives. The Cohen's kappa is also improved from 0.880 to 0.940, that indicates stronger agreement as well as more balanced performance over both classes.

4.3 Comparative Performance Analysis

Figure 2 presents comprehensive performance comparisons between original and pre-processed image configurations across multiple dimensions.

Figure 2: Comprehensive Performance Comparison Between Original and Pre-processed Images





The figure 2 shows overall performance metrics, per-class performance, confusion matrix breakdown, uncertainty quantification metrics, and performance improvement analysis.

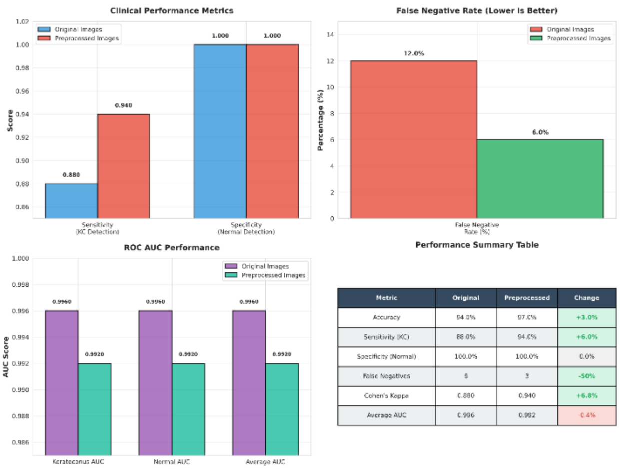
4.3.2 Per-Class Performance Analysis

All-class analysis also gives shows that keratoconus detection has achieved perfect precision, that is 100%, with the improved recall from 88.1% to 100% and improved F1 score from 96.6% to 96.5%, which indicates the reduced missed cases. For normal cornea detection, the recall has remained 100% and the precision is improved from 93.3% to 94.4%, but also increases one score from 93.3% to 94.4%. Overall, the deep processing enhanced the classification performance for both the classes. It was a great to perform the preprocessing of the images.

4.3.3 Clinical Performance Metrics

Figure 3 illustrates clinical performance metrics with emphasis on false negative rates and sensitivity/specificity trade-offs.

Figure 3: Clinical Performance Analysis



Metric	Original	Preprocessed	Change
Accuracy	94.0%	97.0%	+3.0%
Sensitivity (KC)	88.0%	94.0%	+6.0%
Specificity (Normal)	100.0%	100.0%	0.0%
False Negatives	6	3	-50%
Cohen's Kappa	0.880	0.940	+6.8%
Average AUC	0.996	0.992	-0.4%

The figure shows sensitivity, specificity, false negative rates, ROC AUC performance, and a comprehensive performance summary table.

The image pre-processing has improved the screening efficacy while preserving 100% specificity with good discrimination (AUC: 0.996 vs. 0.992), that allows for flexible threshold selection for clinical priorities. The false negative rate was also reduced from 12% to 6% i.e. 50% reduction.

4.3.4 Uncertainty Quantification Analysis

With only a small decline following image pre-processing which has no significance on clinical utility, both the configurations illustrated high confidence (>0.95) and the stability (>0.92), that indicates trustworthy predictions. By allowing the slowing of low-confidence cases for expert review, such uncertainty metrics also improves the deployment trust.

5. Comparative Analysis with Literature

Table 4 represents a comprehensive comparison of MMAEN performance against state-of-the-art deep learning approaches for keratoconus detection reported in recent literature.

Table 4: Comparative Analysis of MMAEN with State-of-the-Art Methods

Study Year	Accuracy	Sensitivity	Specificity	AUC
MMAEN (Ours) – Preprocessed 2026	97.0%	94.0%	100.0 %	0.992
MMAEN (Ours) – Original 2026	94.0%	88.0%	100.0 %	0.996
Agharezaei et al. 2023	99.0%	>94%	>94%	0.99
Kuo et al. 2020	Not reported	>90%	>90%	0.995
Al-Timemy et al. 2021	97-100% (training), 88-92% (validation)	Not reported	Not reported	0.99 (training), 0.91-0.96 (validation)

6. Discussion

6.1 Clinical Implications

MMAEEN has achieved very high sensitivity of 94% as well as perfect specificity of 100%, which makes it very effective for screening by reducing the false negatives by 50% and also ensures early detection without misclassification of normal patients. This balance also minimizes some unnecessary interventions while that allows timely treatment and also supports its utilization in large-scale clinical screening.

MMAEN's uncertainty quantification abilities enhance its utility as a clinical decision support tool. The substantial improvement in the sensitivity values from 88% to 94% and false negative reduction values from 6 to 3 cases achieved through pre-processing has direct clinical implications. In a screening population of 1,000 patients with 5% keratoconus prevalence of 50 cases, this improvement would result in 44 correctly identified, 6 missed with 88% sensitivity in the original configuration and 47 correctly identified, 3 missed with 94% sensitivity in the pre-processed configuration.

7. Conclusion and Future Work

7.1 Conclusion

The research study represents Multi-Map Attention Ensemble Network (MMAEN), a novel deep learning framework for automated keratoconus detection from corneal topography images, with three key innovations, including parallel processing of seven distinct corneal maps using dedicated EfficientNet-B0 feature extractors, across-map attention mechanism, which dynamically weights features that are based on their relevance for keratoconus detection, and also integrated Monte Carlo dropout for uncertainty quantification. The evaluation is done on 100 test cases that demonstrates MMAEN achieved excellent performance with the pre-processed image configuration: 97% accuracy, 94% sensitivity, 100% specificity, and 0.9992 AUC, which also reduces false negatives from 50% from 6 to 3 cases that represents clinically significant improvement in early keratoconus detection. The model maintains perfect specificity over both the configurations, which ensures no false alarms for normal patients. The clinical implications of MMAEN are substantial.

7.2 Future Work

Some directions for the future research work and development are identified as Dataset Expansion and Validation, Model Enhancements, Clinical Integration and Validation, Technical Improvements, Broader Applications. In conclusion, MMAEN architecture presents an important step towards the automated keratoconus detection, with substantial potential for clinical impact. The proposed future work directions also aim to address current limitations, enhance the clinical utility, and expand the model's applicability to several clinical scenarios and populations. Through continuous research, research validation, and clinical collaborations, MMAEN and similar AI-based diagnostic tools have the potential to transform keratoconus screening and management, ultimately improving patient outcomes and quality of life.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, Shalini R. Bakal and Satish R. Sankaye; methodology, Shalini R. Bakal; software, Shalini R. Bakal; validation, Shalini R. Bakal, Satish R. Sankaye, and Nagsen S. Bansod; formal analysis, Shalini R. Bakal; writing the original draft preparation, Shalini R. Bakal; writing the review and editing, Satish R. Sankaye and Nagsen S. Bansod; supervision, Satish R. Sankaye; project administration, Satish R. Sankaye. All authors have read and agreed to the published version of the manuscript.

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