Comparative Analysis of Clinical Corneal Parameters and Deep CNN Features Derived from Corneal Maps

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***Abstract*—The advent of deep convolutional neural networks (CNNs) has revolutionized corneal disease detection, particularly for keratoconus screening. This paper presents a com parative analysis of traditional clinical corneal param eters including K-readings, pachymetry, and elevation maps versus deep CNN derived features extracted from corneal topographic maps. We systematically review recent literature demonstrating that CNN models achieve diagnostic accuracies exceeding 95%, with area under the curve (AUC) values reaching 0.995. While clinical parame ters provide interpretable, standardized measurements, CNN features capture complex spatial patterns that may escape conventional analysis. However, CNN approaches face chal lenges in clinical validation, interpretability, and generalizability. This analysis reveals that hybrid approaches combin ing traditional parameters with CNN derived features, cou pled with explainability methods such as class activation maps, offer the most promising pathway for clinical imple mentation.**

I. INTRODUCTION

Corneal imaging and analysis form the cornerstone of diag nosing and managing various corneal pathologies, with keratoconus being among the most clinically significant conditions requiring early detection. Traditional clinical assessment relies on well-established corneal parameters derived from topographic and tomographic imaging systems, including keratometry readings (K-readings), central corneal thickness (pachymetry), elevation maps, and various curvature indices [1]. These parameters provide standardized, interpretable measurements that guide clinical decisionmaking.

The emergence of deep learning, particularly convolutional neural networks (CNNs), has introduced a paradigm shift in medical image analysis. CNNs possess the ability to automatically learn hierarchical feature representations directly from raw image data, potentially capturing subtle patterns that may not be adequately represented by traditional clinical parameters [2, 3]. Recent studies have demonstrated that CNN-based approaches can achieve diagnostic accuracies exceeding 95% for keratoconus detection, with some models reporting AUC values approaching 0.995 [1, 4].

Despite promising results, several critical questions remain. How do CNN-derived features correlate with established clinical parameters? What specific morphological patterns do CNNs learn? Can CNN approaches generalize across different imaging devices and patient populations?

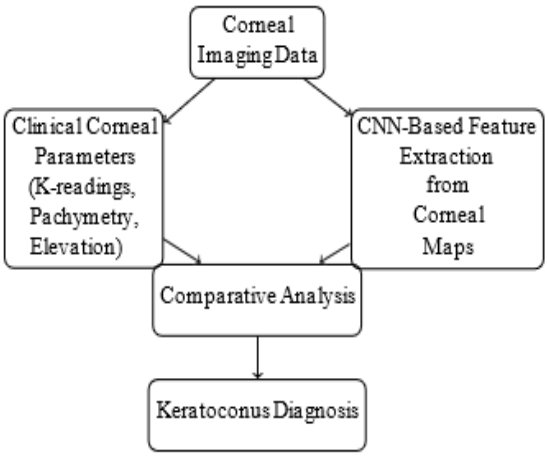

Figure 1: Flow diagram illustrating the comparative analysis between traditional clinical corneal parameters and deep CNN-derived features for keratoconus detection.

This paper addresses these questions through a systematic comparative analysis of clinical corneal parameters and deep CNN features, examining their respective advantages, limitations, and potential for synergistic integration in clinical practice.

II. METHODS

2.1 Literature Review Methodology

This comparative analysis is based on a systematic review of recent literature examining deep learning applications for corneal analysis, with emphasis on keratoconus detection. We focused on studies published between 2019 and 2025 that employed CNN architectures for analyzing corneal topographic or tomographic maps and reported quantitative performance metrics. The review encompassed studies utilizing various imaging modalities, including Pentacam Scheimpflug imaging, Placido disc topography, and anterior segment optical coherence tomography (AS-OCT).

2.2 Clinical Corneal Parameters

Traditional clinical corneal assessment relies on several key parameters. Keratometry readings (K-readings) measure anterior corneal surface curvature. Central corneal thickness (CCT) measured by pachymetry provides information about corneal structural integrity. Elevation maps quantify anterior and posterior corneal surface deviations from reference surfaces [5]. Additional indices include the keratoconus

Table 1: Comparison of Traditional Clinical Corneal Parameters and CNN-Derived Features

Aspect	Clinical Corneal Parameters	CNN-Derived Features
Nature of Features	Explicit, hand-crafted measurements	Automatically learned representations
Examples	K-readings, pachymetry, elevation maps	Deep spatial and texture patterns
Interpretability	High; clinically inter pretable	Limited; requires explainability tools
Sensitivity to Early KC	Moderate	High
Standardization	Well standard-Ized across clinics	Deviceand datasetdependent
Clinical Adoption	Widely used in routine practice	Emerging, research focused

percentage index (KISA%) and inferior-superior asymmetry values. These parameters are typically evaluated using established diagnostic criteria.

2.3 CNN-Based Feature Extraction

Table 2: CNN Architectures and Feature Extraction Approaches in Reviewed Studies

Study	CNN Model	Feature Strategy
Kuo et al. [1]	VGG16, ResNet152	End-to-end classification with CAM
Al-Timemy et al. [2]	Xception, InceptionResNetV2	Deep feature extraction and fusion
Abdelmotaal et al. [4]	CNN-based models	Direct image-based classification
Asharzaei et al. [7]	VGG16	VAE-augmented feature learning
P et al. [20]	CNN + PSO	Preprocessing with optimized segmentation

The reviewed studies employed diverse CNN architectures including VGG16, ResNet152, Xception, InceptionResNetV2, and EfficientNet models [1, 2, 6, 7]. These networks process color-coded corneal maps—including sagittal curvature, elevation, and pachymetry maps—as input images. Several studies employed transfer learning, initializing networks with weights pretrained on ImageNet [3, 8]. Feature extraction strategies varied, with some using CNNs as end-to-end classifiers [1, 4] and others extracting deep features for separate classifiers [2]. Advanced approaches employed feature fusion, combining features from multiple corneal map types [2, 9]. To enhance interpretability, several studies implemented visualization techniques including class activation maps (CAM) [1, 2, 10].

2.4 Performance Evaluation

Table 3: Reported Diagnostic Performance of CNN-Based Keratoconus Detection

Study	Classification Type	Reported Performance
Kuo et al. [1]	Binary	Sensitivity and specificity > 0.90, AUC = 0.995
Al-Timemy et al. [2]	Binary / multi-class	Accuracy = 99.0% (binary), 99.7% (Three-class)
Abdelmotaal et al. [4]	Binary	Sensitivity and specificity > 0.94
Agharezaei et al. [7]	Binary	Accuracy = 99%, AUC=0.99
P et al. [20]	Binary	Accuracy = 95.9%

Studies were evaluated based on standard diagnostic performance metrics including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC). We examined both binary classification (normal vs. keratoconus) and multi-class scenarios (normal vs. subclinical vs. manifest keratoconus).

III. RESULTS

3.1 Performance of CNN-Based Approaches

The reviewed literature demonstrates consistently high diagnostic performance for CNN-based keratoconus detection. Kuo et al. [1] reported that all three tested CNN models achieved sensitivity and specificity exceeding 0.90, with ResNet152 reaching an AUC of 0.995. Al-Timemy et al. [2] demonstrated that feature fusion using Xception and InceptionResNetV2 achieved 99.0% accuracy for binary classification and 99.7% for three-class classification. When features were fed into an SVM classifier, perfect 100% accuracy was achieved on their dataset.

Abdelmotaaletal. [4] reported that CNN models analyzing Scheimpflug camera images achieved sensitivity and specificity consistently above 0.94. Agharezaeietal. [7] demonstrated that augmenting training data using variational autoencoders improved CNN performance, with VGG16 achieving 99% accuracy and AUC of 0.99. P et al. [20] used particle swarm optimization for preprocessing, achieving 95.9% accuracy, substantially outperforming traditional machine learning methods including multilayer perceptron (77.6%), SVM (72%), and decision trees (84%).

IV. DISCUSSION

The comparative analysis reveals that clinical corneal parameters and CNN-derived features offer complementary strengths. Traditional clinical parameters provide standardization across devices, direct physical interpretability, established diagnostic criteria, and compatibility with existing clinical workflows. Conversely, CNN-derived features excel in capturing complex spatial patterns, automatically learning optimal feature representations, integrating information across entire corneal maps, and potentially detecting preclinical disease stages.

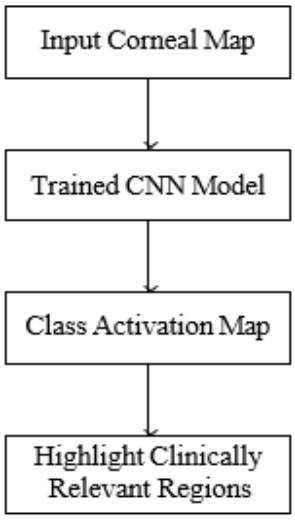

Figure 2: Explainability workflow using class activation maps (CAM) to visualize regions contributing to keratoconus classification.

V. CONCLUSION

This comparative analysis demonstrates that deep CNN features derived from corneal maps achieve superior diagnostic performance compared to traditional clinical parameter-based approaches, with accuracies frequently exceeding 95% and AUC values approaching 0.995 for keratoconus detection. CNN approaches excel at capturing complex spatial patterns and subtle morphological changes. However, traditional clinical parameters retain important advantages in standardization, interpretability, and clinical integration.

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