International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 10 | Oct - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

# A Survey on AI-Based Cornea Detection from Anterior Segment Images

**Prof.Prashant Gawade,Viraj Vishvesh Velani,Aditya Santosh Nivangune , Mayuresh Janardhan Khunte, Sneha Rahul Isave**

Department of AI & Machine Learning, Zeal Polytechnic, Pune
Academic Year: 2026–2027

**Abstract**—Corneal conditions can significantly affect vision, and their clinical assessment commonly relies on anterior-segment imaging. The manual evaluation of these images increasingly demands memory, time, and specialized medical expertise that may exceed resources available in primary care settings. In recent years, computer vision and artificial intelligence (AI) have been extensively investigated to support corneal image analysis, encompassing tasks such as tissue segmentation, screening for selected disorders, and quantitative assessment. This paper presents a comprehensive, extended survey and review of the existing literature on AI-assisted cornea detection, drawing parallels to the resource and scheduling complexities found in distributed computing. We systematically categorize current methodologies into traditional image-processing methods, classical machine learning approaches, and modern deep learning frameworks. Furthermore, we explore image pre-processing strategies, memory and compute constraints on clinical edge devices, and the necessity for rigorous clinical validation. Finally, we propose a modular, adaptive workflow suitable for edge prototyping and discuss future research directions to enhance the robustness, explainability, and deployment of these diagnostic support systems in heterogeneous clinical environments.

## I. INTRODUCTION

The cornea is the transparent front surface of the eye, responsible for focusing a significant portion of incoming light. Alterations in its shape, transparency, thickness, or cellular structure are frequently indicative of underlying ocular conditions, such as keratoconus, corneal dystrophies, and infections. Traditionally, clinicians evaluate these conditions using a variety of imaging techniques, including slit-lamp photography, corneal topography, and anterior-segment optical coherence tomography (AS-OCT)[cite: 3].

As the volume of ophthalmic imaging data grows, the manual assessment of these images becomes increasingly time-consuming and subjective. The computational cost of running advanced diagnostic models on high-resolution medical imagery is shaped by parameter count, numerical precision, and the memory required to retain intermediate imaging state. Consequently, computer-aided cornea detection has garnered substantial attention from both the medical and artificial intelligence communities. In this context, “cornea detection” encapsulates several distinct tasks: (a) locating the broad corneal region within an image, (b) precisely segmenting its boundaries or specific cellular layers, and (c) screening for targeted diseases based on morphological features[cite: 3].

The challenge is especially important for clinical edge environments. Hospital hardware may include different GPU generations, integrated graphics, varying memory capacities, and different operating systems. A model that is too large for a local clinical machine may need to be executed using memory offloading, quantization, or a hosted inference service. Each option trades cost, latency, privacy (e.g., patient data transmission), and operational complexity.

While several reviews exist in the broader field of ophthalmic AI, this survey specifically narrows its focus to anterior segment image analysis for cornea detection under resource-constrained clinical settings. We propose a taxonomy that categorizes the literature into distinct methodological levels: Traditional Image Processing, Classical Machine Learning, and Deep Learning approaches[cite: 3]. Furthermore, we outline a student-level proposed workflow to serve as a foundational prototype for further research.

## II. BACKGROUND AND PROBLEM FORMULATION

### A. Corneal Imaging Modalities

The efficacy of any computer-aided detection system is fundamentally tied to the quality and nature of the input data. In corneal assessment, several imaging modalities are utilized, each providing unique structural insights[cite: 3]:

- Slit -lamp Photography: This modality provides high-resolution, visible-light views of the anterior eye. It is the most common diagnostic tool for identifying surface features, ulcers, or gross opacities[cite: 3].
- Corneal Topography and Tomography: These techniques map the surface curvature and elevation of the cornea. They are critical for diagnosing shape-related abnormalities, such as keratoconus, by providing quantitative shape-related measurements[cite: 3].
- Anterior -Segment OCT (AS-OCT): AS-OCT utilizes low-coherence interferometry to produce high-resolution, cross-sectional images of the anterior segment. It is highly useful for structural measurement, assessing corneal thickness (pachymetry), and layer boundary segmentation[cite: 3].
- In-vivo Confocal Microscopy (IVCM): IVCM provides non-invasive, high-magnification images of corneal cellular structures and sub-basal nerves, allowing for the micro-structural evaluation of the cornea in real-time[cite: 3].

It is crucial to note that models trained on one specific modality exhibit a domain gap and cannot automatically be assumed to generalize to another without domain adaptation techniques[cite: 3].

### B. Clinical Deployment Constraints

In clinical pipelines, high-resolution AS-OCT images represent a significant memory footprint. A single 3D

volumetric scan can exceed the VRAM of standard consumer GPUs. Processing these scans autoregressively or in large batches for segmentation requires careful scheduling. Let D be the set of available diagnostic devices in a clinic; matching the computational requirement of a deep neural network to the appropriate hardware di is a scheduling challenge analogous to distributed LLM inference, requiring optimization of memory use and communication latency if data is processed via a hospital network.

## III. SURVEY METHODOLOGY

This draft uses a structured narrative comparison of representative primary papers and survey articles. The initial candidate corpus covers corneal image segmentation, keratoconus screening, layer extraction from AS-OCT, and edge-deployed medical inference. The selection is intended to provide architectural coverage rather than claim an exhaustive systematic review.

For each paper, the comparison records: (i) target imaging modality; (ii) model architecture; (iii) resource or network assumptions; (iv) feature extraction strategy; (v) diagnostic objective; and (vi) reported evaluation measures. A full systematic review should extend this draft by searching digital libraries using documented query strings and applying explicit inclusion criteria.

## IV. TAXONOMY OF CORNEA DETECTION METHODS

To systematically understand the landscape of AI in cornea detection, we categorize the existing literature based on their core algorithmic approach. This taxonomy divides the field into three primary branches[cite: 3]:

### A. Traditional Image Processing Methods

Before the advent of deep learning, corneal region localization heavily relied on traditional image processing pipelines[cite: 3]. These pipelines typically sequence several deterministic algorithms to isolate the region of interest. Common techniques include intensity normalization, adaptive thresholding, and histogram equalization to counter varying illumination[cite: 3]. Edge detection operators (such as Canny or Sobel) are frequently employed to locate the epithelial and endothelial boundaries in AS-OCT images. Mathematical morphology (dilation, erosion) and geometric constraints (such as Hough transforms for circular iris/cornea boundaries) are then applied to refine the masks[cite: 3].

While these methods are computationally fast and highly interpretable, they lack robustness[cite: 3]. They often fail in the presence of strong light reflections, motion blur, low contrast, or anatomical variations across different imaging devices[cite: 3].

### B. Classical Machine Learning

Classical Machine Learning (ML) serves as an intermediate step, relying on handcrafted feature extraction followed by statistical classification[cite: 3]. In these systems, domain experts design features such as texture descriptors (e.g., Haralick features, Local Binary Patterns), geometric parameters (thickness, curvature), and frequency-domain representations[cite: 3].

These features are fed into classifiers such as Support Vector Machines (SVM), Random Forests (RF), or k-Nearest Neighbors (k-NN) to classify the image (e.g., normal vs. keratoconic)[cite: 3]. Performance in this paradigm is heavily dependent on the quality of the feature engineering[cite: 3]. While they perform well on modest, structured datasets, they struggle to capture the complex, non-linear hierarchical representations required for generalized image understanding[cite: 3].

### C. Deep Learning Approaches

Deep learning (DL) has emerged as the dominant paradigm for cornea detection, driven by the ability of Convolutional Neural Networks (CNNs) to learn hierarchical visual features directly from raw pixel data[cite: 3].

1) Segmentation Architectures: For tasks requiring precise boundary delineation, such as isolating the cornea in an AS-OCT scan, fully convolutional networks are the standard. The U-Net architecture, characterized by its symmetric encoder-decoder structure and skip connections, is extensively utilized. It allows for high-resolution, pixel-level masks, albeit requiring labor-intensive pixel-level annotations for training[cite: 3].

2) Classification Networks: For disease screening tasks (e.g., detecting keratoconus from topography maps), standard CNN architectures (such as ResNet, VGG, or DenseNet) are frequently adapted. These networks output a probability score indicating the presence or severity of a specific disorder. While highly accurate, these models are often criticized as "black boxes," making clinical interpretability a challenge[cite: 3].

## V. RESOURCE SCHEDULING AND MEMORY OPTIMIZATIONS

### A. Activation and Feature Map Transfer

In layer-wise pipeline processing of high-resolution medical images, large feature maps are generated. Network round-trip latency and software overhead matter when hospitals rely on centralized servers for inference. A scheduler must account for the transfer of large DICOM or TIFF files between the imaging edge device and the compute server, minimizing latency for real-time diagnostic support.

### B. Compression and Quantization

Reducing activation precision (e.g., INT8 quantization) can lower the memory footprint of U-Net models on clinical edge devices, at the cost of potential numerical artifacts in pixel-level boundary masks. Compression should be evaluated end-to-end: a smaller payload is beneficial only if diagnostic sensitivity and specificity remain unaffected.

## VI. COMPARATIVE ANALYSIS OF EXISTING APPROACHES

Different methodologies present distinct trade-offs regarding interpretability, data requirements, and robustness. Table 1 summarizes the comparative advantages and limitations of the discussed approaches[cite: 3].

| Methodology | Advantages | Limitations |
|---|---|---|

| | | |
|---|---|---|
| Traditional Image Processing | Simple, computationally lightweight, highly interpretable. | Extremely sensitive to image quality, reflections, and parameter tuning. |
| Classical Machine Learning | Works reasonably well on small, structured datasets. | Performance is bounded by the quality of handcrafted feature engineering. |
| Deep Learning (Segmentation) | Produces precise, pixel-level boundary masks. | Requires extensive pixel-level ground truth data; computationally heavy. |
| Deep Learning (Classification) | Learns complex, abstract patterns for accurate disease screening. | "Black box" nature hinders explainability; requires large annotated datasets. |
| Hybrid Pipelines | Modular, practical, incorporates explicit quality checks. | Complex to orchestrate and validate end-to-end. |

Table 1: Comparison of Methodologies for Cornea Detection[cite: 3]

## VII. EVALUATION METRICS

The selection of appropriate metrics is vital for objective evaluation. For region localization and segmentation, the Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) are standard[cite: 3]. For screening and classification tasks, Sensitivity, Specificity, Precision, F1-score, and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC) are preferred[cite: 3]. Accuracy alone is frequently misleading due to the inherent class imbalance in medical datasets[cite: 3].

## VIII. OPEN CHALLENGES AND RESEARCH DIRECTIONS

Despite significant progress, the deployment of AI for cornea detection faces several hurdles[cite: 3]:

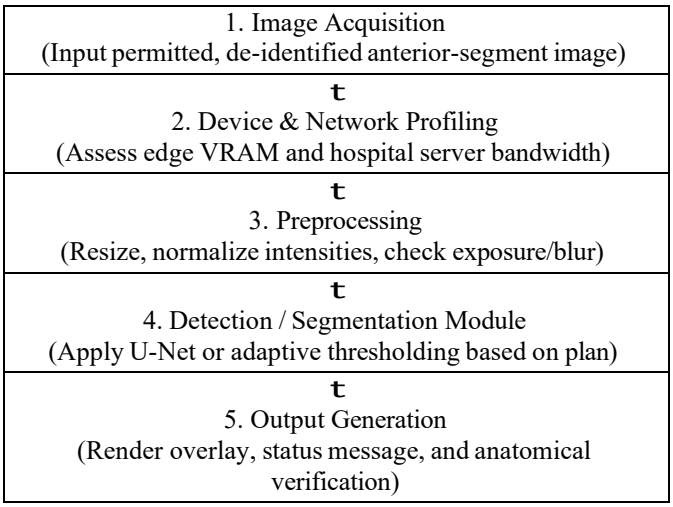
- Data Scarcity and Diversity: There is a distinct lack of large, publicly available, diverse, and well-annotated anterior-segment image datasets[cite: 3].
- Generalization: Models trained on data from one specific clinical device or demographic often suffer severe performance degradation when tested on external datasets[cite: 3].
- Explainability: The opaque decision-making processes of deep neural networks limit trust among clinicians[cite: 3].
- Methodological Flaws: Many studies fail to isolate training and test datasets at the patient level, leading to data leakage and inflated performance metrics[cite: 3].
- Resource Constraints: Running complex deep learning models on local clinical workstations often faces memory bottlenecks, necessitating adaptive execution plans akin to distributed inference frameworks.

## IX. PROPOSED SYSTEM WORKFLOW

Based on the literature reviewed, we propose a modular, hybrid pipeline suitable for student-level prototyping. This workflow is intended for research and educational purposes and acts as a decision support tool rather than an independent diagnostic agent. By borrowing concepts from communication-aware scheduling, this workflow evaluates local vs. cloud execution based on real-time device profiling.

**[ Figure 1: Block Diagram of the Proposed AI-Based Cornea Detection System ]**

*(Illustrating the end-to-end process from image acquisition to the final output)*




- Step 1 — Image Acquisition: Input a permitted, de-identified anterior-segment image from a local modality.
- Step 2 — Device & Network Profiling: The system assesses the clinical edge device's available VRAM and the network bandwidth to the centralized hospital server.
- Step 3 — Preprocessing: Resize images to a standard resolution, normalize pixel intensities, and execute automated quality checks for blur and exposure locally.
- Step 4 — Execution Plan Selection: If local memory allows, process entirely on the edge device to preserve privacy. Otherwise, compress and transmit to the hospital cloud.
- Step 5 — Detection/Segmentation Module: Apply either a tuned baseline image-processing algorithm (e.g., adaptive thresholding) or a pre-trained deep learning segmentation model (e.g., a lightweight U-Net variant), depending on the availability of labeled data.
- Step 6 — Post-processing: Remove artifacts using morphological operations and verify the anatomical plausibility of the detected region.
- Step 7 — Output Generation: Render the original image overlaid with the detected region alongside a basic quality or status message via a user interface (e.g., built with Streamlit).

## X. CONCLUSION

AI and computer vision possess substantial potential to support and streamline corneal image analysis[cite: 3]. The

optimal approach depends strictly on the clinical task: region localization, boundary segmentation, structural measurement, or disease screening[cite: 3]. While traditional methods offer simplicity, modern deep learning architectures provide superior pattern recognition capabilities at the cost of requiring massive labeled datasets and substantial compute resources[cite: 3]. Future research must prioritize multi-device validation, adaptive resource scheduling for edge deployments, uncertainty estimation, and the integration of explainable AI frameworks to facilitate real-world clinical adoption[cite: 3].

## ACKNOWLEDGMENT

The authors express their sincere gratitude to Prof. Prashant Gawade, Project Guide, for her valuable guidance. The authors also extend their thanks to Prof. Vaishnavi Patharwat, Head of Department (HOD), and to Prof. Vijay Mohite, Principal of Zeal Polytechnic, for providing the academic environment and institutional support necessary to pursue this work.

## REFERENCES

[1] Hezekiah, J. D. K., & Chacko, S. (2020). “A Review on Cornea Imaging and Processing Techniques.” Current Medical Imaging, 16(3), 181-192.

[2] Tey, K. Y., Cheong, E. Z. K., & Ang, M. (2024). “Potential applications of artificial intelligence in image analysis in cornea diseases: a review.” Eye and Vision, 11, 10.

[3] Tahvildari, M., Singh, R. B., & Saeed, H. N. (2021). “Application of Artificial Intelligence in the Diagnosis and Management of Corneal Diseases.” Seminars in Ophthalmology, 36(8), 641-648.

[4] Nguyen, T., et al. (2024). “Artificial Intelligence in Corneal Diseases: A Narrative Review.” Contact Lens and Anterior Eye, 47(6), 102284.

[5] Bodmer, N. S., et al. (2024). “Deep Learning Models Used in the Diagnostic Workup of Keratoconus: A Systematic Review and Exploratory Meta-Analysis.” Cornea, 43(7), 916-931.

[6] Ronneberger, O., Fischer, P., & Brox, T. (2015). “U-Net: Convolutional Networks for Biomedical Image Segmentation.” MICCAI, 234-241.