Application of Artificial Intelligence in the Diagnosis of Contact Lens-Induced Dry Eye: A Narrative Review

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Abstract: ***Contact lens induced dry eye (CLIDE) represents a significant clinical challenge in optometric and ophthalmic practice, often leading to discomfort, reduced the wearing time, and discontinuation of contact lens use. Conventional diagnostic approaches rely on subjective symptom assessment and examiner-dependent measurements such as tear break-up time (TBUT), tear meniscus height (TMH), and meibography grading. These methods are though limited by variability and lack of reproducibility. Artificial intelligence (AI), particularly machine learning and deep learning techniques, has recently demonstrated substantial promise in the objective evaluation of ocular surface parameters associated with dry eye disease. This narrative review synthesizes contemporary literature on AI-based diagnostic tools relevant to CLIDE, including automated meibomian gland segmentation, non-invasive TBUT detection, tear meniscus quantification, proteomic classification, and predictive modelling. Although most studies focus on general dry eye populations, the diagnostic targets directly overlap with mechanisms implicated in contact lens intolerance. AI-driven systems demonstrate high segmentation accuracy, strong agreement with manual measurements, and potential for large-scale phenotyping. With further validation in contact lens–specific cohorts, AI technologies may enhance early detection, improve monitoring, and support personalized management strategies in CLIDE.***

Keywords: contact lens induced dry eye, artificial intelligence, deep learning, meibomian gland dysfunction, tear film instability

1. Introduction

Contact lenses are widely prescribed medical devices used for refractive correction, therapeutic purposes, and cosmetic enhancement (Gurnani & Kaur, 2025). Despite technological advances in lens materials and surface treatments, discomfort related to tear film instability remains one of the leading causes of contact lens discontinuation. Contact lens induced dry eye (CLIDE) is characterized by symptoms of dryness, burning, fluctuating vision, and foreign body sensation, often associated with tear film disruption and meibomian gland dysfunction.

The pathophysiology of is multifactorial. Lens placement divides the tear film into pre-lens and post-lens compartments, altering its natural dynamics (Kojima, 2018). Increased evaporation, mechanical interaction during blinking, and inflammatory responses contribute to tear instability. Soft contact lens wear has also been associated with structural changes in meibomian glands, including dropout and altered visibility (García-Marqués et al., 2022). These alterations compromise the lipid layer, further accelerating evaporation.

Traditionally diagnosis relies on symptom-based questionnaires and clinical tests such as fluorescein TBUT, slit-lamp based tear meniscus estimation, and subjective meibography grading (Markoulli & Kolanu, 2017). However, these assessments are mostly examiner-dependent and susceptible to variability.

Artificial intelligence (AI) has emerged as a transformative tool in ophthalmology, offering automated image analysis, objective quantification, also predictive modelling capabilities (Ji et al., 2022; Harti et al., 2025). Although most AI applications mainly target general dry eye disease (DED), the structural and functional parameters assessed overlap substantially with mechanisms underlying Contact Lens Induced dry eye. This narrative review synthesizes current evidence on AI-based diagnostic approaches relevant to contact lens associated tear dysfunction.

2. Method

This narrative review synthesizes peer-reviewed literature that has been published between 2018 and 2025 that examined applications of artificial intelligence in the diagnosis and evaluation of dry eye disease. A structured literature search was conducted using electronic databases and journal archives. Search terms included combinations of “artificial intelligence”, “deep learning”, “machine learning”, “meibomian gland”, “tear break-up time”, “tear meniscus height”, and “contact lens dry eye.” Boolean operators (and, or) were applied to refine the search and identify studies relevant to ocular surface diagnostics.

Studies were considered eligible for inclusion if they have evaluated artificial intelligence-based methodologies, including machine learning or deep learning models, and if they focused on imaging parameters or tear film metrics relevant to contact lens induced dry eye. Only articles published in peer-reviewed journals and available in

English were included. Although many identified studies examined general dry eye disease populations, their findings were interpreted within the context of contact lens associated tear instability, given the shared pathophysiological mechanisms underlying these conditions.

Table 1: Summary of Artificial Intelligence Applications Relevant to Contact Lens–Induced Dry Eye

Author (Year)	Journal	Study Type	AI Approach	Target Parameter	Reported Performance	Relevance to CLIDE
Setu et al. (2021)	Scientific Reports	Retrospective imaging	CNN segmentation	Meibomian gland morphology	High precision and recall	Detects gland dropout linked to lens intolerance
Li et al. (2023)	Scientific Reports	Retrospective	Unsupervised DL (U-Net)	Meibography clustering	Large-scale phenotyping	Identifies gland dysfunction subtypes
Shimizu et al. (2023)	Translational Vision Science & Technology	Retrospective	ML regression	Tear break-up time	AUC = 0.877	Objective tear instability detection
Abdelmotaal et al. (2023)	American Journal of Ophthalmology	Retrospective cohort	CNN	Ocular surface video	AUC ≈ 0.98	Automated DED detection
Wang et al. (2023a)	Investigative Ophthalmology & Visual Science	Cross-sectional	AI segmentation	Tear meniscus height	Strong correlation with manual	Tear volume quantification
Wang et al. (2023b)	Journal of Clinical Medicine	Imaging study	Deep neural network	Meibomian grading	High diagnostic accuracy	Standardized gland grading
Kikukawa et al. (2023)	PLoS ONE	Diagnostic study	CNN	Non-invasive TBUT	Strong agreement	Tear film stability monitoring
Fineide et al. (2023)	Scientific Reports	Proteomic ML	Random Forest	Tear protein classification	High classification precision	Biomarker-linked gland dysfunction
Graham et al. (2024)	Ophthalmology Science	Cross-sectional	DL + ML	MG morphology & prediction	65–99% accuracy	Predicts functional tear changes
Nejat et al. (2024)	Ophthalmology Science	Prospective imaging	Deep learning	Smartphone TMH	Automated measurement accuracy	Accessible screening model
Fernández-Jiménez et al. (2025)	Contact Lens & Anterior Eye	Comparative	SVM, RF, KNN	MG alterations	>79% classification accuracy	Direct CL wear population relevance
Yu et al. (2025)	Frontiers in Medicine	Imaging analysis	DL segmentation	Infrared meibography	High segmentation metrics	Quantitative MG evaluation

Artificial Intelligence in Meibomian Gland Assessment

Meibomian gland dysfunction is central to evaporative tear instability in contact lens wearers (Kojima, 2018). Automated segmentation techniques have significantly enhanced morphological assessment. Setu et al. (2021) developed a convolutional neural network (CNN) which is capable of segmenting meibomian glands with high precision and recall. This model enabled quantitative gland area measurement, reducing observer-dependent grading variability. Similarly, Wang et al. (2023b) applied deep neural networks for standardized gland grading, demonstrating strong diagnostic accuracy. Yu et al. (2025) further refined infrared meibography segmentation using deep learning techniques, reporting robust segmentation metrics.

Fineide et al. (2023) expanded the scope of diagnosis beyond imaging, employing Random Forest algorithms to classify meibomian gland dysfunction based on tear proteomics. This approach suggests potential integration of structural and biochemical diagnostics.

Importantly, Fernández-Jiménez et al. (2025) evaluated machine learning classification specifically in contact lens wearers, achieving classification accuracies exceeding 79% in distinguishing gland alterations between wearers and controls. This direct relevance strengthens the translational value of AI for CLIDE.

Artificial Intelligence in Tear Film Stability Assessment

Tear break-up time remains a core indicator of tear film instability but suffers from variability (Markoulli & Kolanu, 2017). Shimizu et al. (2023) applied machine learning regression to estimate TBUT, reporting an AUC of 0.877. Kikukawa et al. (2023) introduced a CNN-based automated noninvasive TBUT detection system, demonstrating strong agreement with conventional measurements. Abdelmotaal et al. (2023) achieved an AUC approaching 0.98 in automated DED detection using deep learning analysis of ocular surface videos.

Artificial Intelligence in Tear Volume Quantification

Tear meniscus height reflects tear volume status. Wang et al. (2023a) demonstrated strong correlations between AI-based segmentation and manual TMH measurements. Nejat et al. (2024) extended this concept through smartphone-based deep learning TMH assessment, suggesting accessible screening potential. Objective TMH monitoring may be particularly useful in identifying tear deficiencies contributing to contact lens discomfort.

Phenotypic Subclassification and Predictive Modelling

Li et al. (2023) utilized unsupervised deep learning to identify imaging-based DED subtypes through large-scale clustering. This phenotypic approach may enable stratified management in contact lens wearers exhibiting heterogeneous tear dysfunction patterns. Graham et al.

(2024) combined deep learning segmentation with predictive modeling to estimate functional tear changes, reporting accuracy ranging from 65% to 99% depending on task specificity. Such predictive systems may facilitate early identification of individuals at risk of lens intolerance. Reviews by Ji et al. (2022) and Harti et al. (2025) emphasize AI's expanding diagnostic performance and scalability in ocular surface disease.

3. Discussion

Artificial intelligence based diagnostic approaches are rapidly transforming the assessment of ocular surface disorders. Although most of the current models have been developed specifically for general dry eye disease (DED), their clinical relevance to contact lens induced dry eye (CLIDE) is substantial, given the shared pathophysiological mechanisms of tear instability and meibomian gland dysfunction.

a. Clinical Significance in Contact Lens Practice

Contact lens wear disrupts tear film architecture, accelerates evaporation, and may induce morphological alterations in meibomian glands (Kojima, 2018; García-Marqués et al., 2022). Traditional diagnostic methods, including fluorescein TBUT, slit-lamp estimation of tear meniscus height, and subjective meibography grading, are inherently examiner-dependent and prone to variability (Markoulli & Kolanu, 2017). AI-driven segmentation and classification systems directly address these limitations by introducing standardization and automation. For example, automated meibomian gland segmentation models (Setu et al., 2021; Wang et al., 2023b; Yu et al., 2025) enable objective quantification of gland dropout, a structural marker strongly associated with evaporative tear instability. In contact lens wearers, early detection of gland compromise could facilitate timely modification of lens material, wearing schedule, or lubrication strategies before symptom escalation. Similarly, AI-based TBUT estimation systems (Shimizu et al., 2023; Kikukawa et al., 2023) offer reproducible tear stability measurements without reliance on examiner interpretation. This is particularly valuable in CLIDE, where subtle instability may precede overt corneal staining or severe symptoms. Automated tear meniscus height quantification (Wang et al., 2023a) and smartphone-based deep learning tools (Nejat et al., 2024) further expand accessibility and scalability of tear assessment. Such models could potentially support tele-ophthalmology screening programs or chairside screening in high-volume optometry clinics.

b. From Detection to Prediction

A notable advancement in AI applications is the shift from parameter measurement to predictive modelling. Graham et al. (2024) demonstrated that combining deep learning segmentation with machine learning prediction can very well estimate functional tear changes based on morphological features. This transition toward predictive analytics may eventually help in enabling risk stratification models for contact lens intolerance. Furthermore, unsupervised learning approaches (Li et al., 2023) introduce the possibility of phenotypic subclassification. Contact lens related dry eye is unlikely to be a homogeneous condition; instead, patients or wearers may exhibit varying combinations of aqueous deficiency, evaporative instability, or gland dropout. AI-driven clustering may allow clinicians to tailor management strategies more precisely. Proteomic machine learning models (Fineide et al., 2023) further indicate that integration of imaging and biochemical biomarkers could enhance diagnostic depth. Although currently exploratory, such multimodal AI systems may represent the next stage in precision ocular surface medicine.

Strengths of AI Integration

The evidence synthesized in this review underscores several important advantages of integrating artificial intelligence into ocular surface diagnostics. Compared with traditional manual grading approaches, AI-based systems enhance reproducibility and minimize examiner-dependent variability. Automated segmentation and classification algorithms enable objective and quantitative assessment of structural parameters such as meibomian gland morphology and tear film metrics, reducing subjectivity inherent in conventional clinical interpretation. In addition, these systems can obviously process large datasets efficiently, making them suitable for high-volume clinical settings and large-scale phenotyping studies. The potential integration of AI algorithms into clinical decision-support systems further expands their utility, allowing real-time analysis and standardized reporting.

Comprehensive evaluations of AI applications in ocular surface disease (Ji et al., 2022; Harti et al., 2025) indicate that many models achieve diagnostic performance comparable to, and in some cases exceeding, conventional clinical assessment. In the context of contact lens practice, such advancements may facilitate earlier identification of tear instability and gland dysfunction, thereby support proactive management strategies and potentially improve long-term lens tolerance and patient retention.

4. Limitations and Challenges

Despite the encouraging performance reported across studies, several important limitations warrant consideration. A substantial proportion of current AI models are derived from retrospective datasets collected under controlled conditions. As a result, their generalizability to broader and more diverse clinical populations, particularly long-term contact lens wearers, remains uncertain. Prospective validation in real-world settings is still limited.

In addition, many existing systems are designed to distinguish between the presence and absence of dry eye disease rather than to identify contact lens–specific subtypes. Given that contact lens–induced dry eye may represent a distinct clinical phenotype, the lack of dedicated CLIDE-focused datasets restricts the immediate translational applicability of these tools.

Algorithm transparency also remains a concern. Deep learning systems, particularly convolutional neural networks, are often perceived as "black-box" models, providing limited insight into the features driving their predictions. This opacity may contribute to clinician hesitation and underscores the need for explainable AI frameworks.

Practical considerations further influence implementation. Integration into routine clinical workflows requires compatibility with existing imaging devices, appropriate training infrastructure, and careful cost–benefit evaluation. Moreover, regulatory standards governing AI-based ophthalmic technologies continue to evolve, and compliance requirements may affect the pace of clinical adoption.

5. Ethical and Practicality Considerations

The integration of artificial intelligence into clinical practice must be guided by clear ethical and professional standards. Safeguarding patient data privacy, ensuring informed consent when AI-based analytical tools are used, and maintaining transparency in reporting algorithm performance are fundamental considerations. While automated systems can enhance efficiency and standardization, they should complement rather than replace clinical judgment. Excessive reliance on algorithmic outputs without appropriate clinical correlation may introduce unintended risks.

Equity of access also warrants attention. Advanced imaging platforms required for some AI applications may not be readily available in all practice settings, particularly in resource-limited environments. If not carefully implemented, such disparities could widen existing gaps in eye care delivery. Encouragingly, the development of smartphone-based diagnostic tools (Nejat et al., 2024) suggests a pathway toward more accessible and scalable solutions, potentially supporting broader and more equitable screening strategies.

6. Future Directions

Future investigations should focus on strengthening the clinical applicability of artificial intelligence in contact lens induced dry eye. Prospective validation studies conducted in contact lens specific populations are necessary to confirm generalizability beyond controlled research datasets. The development of multimodal AI frameworks that integrate imaging findings with clinical signs and patient-reported symptom scores may provide a more comprehensive representation of tear dysfunction. Longitudinal studies are also needed to evaluate whether algorithm-derived parameters can predict lens intolerance over time. Advances in explainable AI methodologies will be important to enhance clinician confidence and facilitate responsible implementation. Furthermore, formal cost-effectiveness analyses within real-world clinical environments will help determine the practical value of incorporating these technologies into routine care. Integration with electronic health records may further strengthen predictive modeling capabilities and support more individualized lens prescription and follow-up strategies.

7. Conclusion

Artificial intelligence based diagnostic approaches represent a significant advancement in the evaluation of tear film instability and meibomian gland dysfunction. Although most current evidence derives from general dry eye populations, the diagnostic parameters targeted by AI systems directly overlap with the pathophysiological mechanisms underlying contact lens–induced dry eye.

Automated segmentation, objective TBUT estimation, tear meniscus quantification, and predictive modeling collectively demonstrate high diagnostic performance and improved reproducibility. With appropriate validation in contact lens–specific cohorts, AI-driven tools have the potential to transform screening, monitoring, and personalized management of contact lens–related tear dysfunction.

Continued interdisciplinary collaboration between clinicians, data scientists, and regulatory bodies will be essential to ensure safe, effective, and equitable implementation of these technologies in ocular surface care.

Conflict of Interest

There was no conflict of interest.

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