International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 12 | Dec - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

AI-Based Early Detection System for Dry Eye Disease with Automated Humidifier Control

Anchitha C. M., Binza Mariyam, Sara S, Suthika B.
LBS Institute of Technology for Women, Poojappura, Thiruvananthapuram, Kerala, 695012, India

Abstract

Dry Eye Disease (DED) detection in current clinical practice relies heavily on manual diagnosis, patient-reported symptoms, and periodic eye examinations, often requiring specialized equipment and trained personnel. Existing wearable solutions, while effective, are expensive and impractical for continuous, everyday use. This work proposes a cost-effective, non-invasive, and scalable system for real-time DED monitoring using a standard webcam and computer vision algorithms such as MediaPipe Face Mesh and Eye Aspect Ratio detection. The system continuously analyzes blink patterns to identify abnormal blink rates indicative of dry eye conditions. Upon detection, it automatically activates a connected humidifier to restore optimal air moisture levels, providing preventive intervention. Designed for seamless background operation, the solution is suitable for home, office, and multi-user environments, offering an affordable alternative to existing methods while integrating health monitoring with environmental control.

Keywords: Blink rate analysis, Computer vision, Dry Eye Disease (DED), Health monitoring, Automated humidifier control

Introduction

Dry Eye Disease (DED) is a prevalent and multifactorial ocular disorder that affects millions of people globally, with its incidence steadily increasing in the modern digital era.

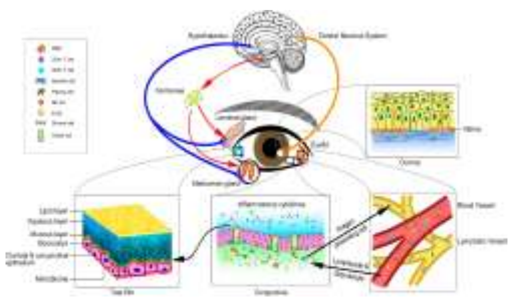

Figure 1: Diagram illustrating the complex neuro-immune-endocrine interactions that regulate tear film homeostasis and contribute to the inflammation and pathology of Dry Eye Disease (DED).

The condition is particularly common among individuals who spend extended hours using digital devices such as computers, smartphones, and tablets. Prolonged screen exposure leads to reduced blink frequency and incomplete blinking, which disrupts the tear film and accelerates tear evaporation. As a result, individuals experience symptoms such as dryness, burning sensations, irritation, redness, and a persistent feeling of grittiness in the eyes.

In severe cases, DED can significantly impair vision quality and reduce overall productivity and quality of life. The tear film, which serves as the eye's first line of defense, is composed of three essential layers—lipid (oily), aqueous (watery), and mucin (mucous). Each layer plays a crucial role in maintaining ocular surface lubrication, nutrient supply, and optical clarity. Any imbalance in these layers can compromise tear film stability, leading to inflammation and damage to the corneal surface. Environmental factors such as air conditioning, low humidity, pollution, and prolonged contact lens wear further exacerbate the condition.

Early detection and preventive management of DED are therefore essential to avoid chronic discomfort and potential complications. Traditional diagnostic methods rely on clinical tests such as the Schirmer test, tear breakup time (TBUT), and ocular surface staining. However, these are often invasive, time-consuming, and unsuitable for continuous monitoring outside clinical settings.

In this study, we propose an intelligent, AI-based system that uses a standard webcam to monitor facial features and analyze blink patterns in real time. The system employs computer vision algorithms to detect eye landmarks and calculate blink rates, which serve as indicators of ocular dryness. When the blink rate deviates from the normal range, the system automatically activates an ultrasonic humidifier to regulate ambient moisture levels. A companion mobile application synchronizes with the system to provide live updates, personalized recommendations, and data visualizations related to eye health.

By integrating artificial intelligence with simple, cost-effective hardware, this approach offers a practical and user-friendly solution for early detection and self-management of Dry Eye Disease. It has potential applications in both home and workplace environments, promoting healthier digital habits and improving overall ocular wellness.

Methodology

The proposed system integrates computer vision, embedded hardware control, and a cross-platform monitoring application to form a complete early detection and response framework.

Dry Eye Detection Framework

The detection mechanism utilizes a standard webcam to capture real-time facial video and employs computer vision techniques to estimate blink rates. The captured video stream is processed frame by frame to detect and monitor subtle variations in eyelid movement, allowing accurate quantification of blink frequency and duration. This non-invasive and low-cost setup makes the system suitable for continuous monitoring in real-world environments.

Facial Landmark and Eye Tracking

- **Video Capture:** Continuous facial video is acquired using a standard webcam under normal lighting conditions. The live stream is processed in real time, ensuring minimal latency and efficient frame handling for continuous eye activity monitoring.
- **Landmark Detection:** The **MediaPipe Face Mesh** model is employed to detect and map **468 facial landmarks**, providing precise localization of key facial regions, including both eyes, eyelids, and surrounding contours. This dense landmark mapping enables accurate tracking even with minor head movements or variations in facial orientation.
- **Eye Aspect Ratio (EAR) Calculation:** Specific landmark coordinates around the left and right eyes are extracted to compute the **Eye Aspect Ratio (EAR)**, a geometric measure representing the ratio between vertical eye height and horizontal width. A sudden drop in EAR indicates eyelid closure, which is used to detect blink onset and completion. Continuous EAR computation across frames allows estimation of **blink rate**, **duration**, and **completeness**.
- **Noise Handling:** To enhance robustness, temporal smoothing and filtering techniques are applied to minimize false detections caused by lighting changes, facial expressions, or transient head motion.
- **Output Metrics:** The processed EAR data is used to compute average blink rate per minute, identify abnormal blinking patterns, and classify the condition as normal or indicative of **Dry Eye Disease (DED)**.

The EAR is computed as:

$$EAR = \frac{(|p_2 - p_6| + |p_3 - p_5|)}{2 \times |p_1 - p_4|}$$

where p_i are the 2D coordinates of the corresponding eye landmarks.

Figure 2: Illustration of the six facial landmarks (p_1 to p_6) used to calculate the **Eye Aspect Ratio (EAR)** for determining the open or closed state of the eye. The EAR is a key metric in computer vision for blink detection, calculated as the ratio of the vertical distance between the eye landmarks to the horizontal distance. An **open eye** (left) has a higher EAR, while a **closed eye** (right) results in a lower EAR, approaching zero

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 12 | Dec - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

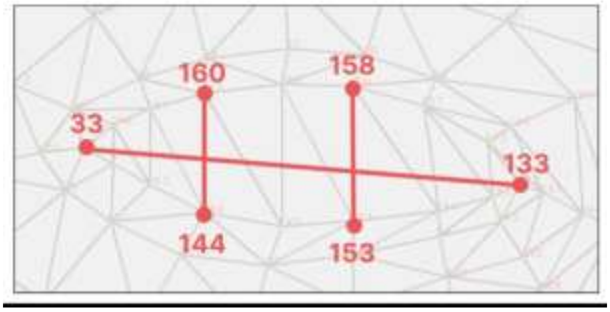

Figure 3: Eye landmarks detected using Eye Aspect Ratio (EAR).

Blink Detection and Classification

- **Blink Identification:** A blink is identified when the Eye Aspect Ratio (EAR), computed from the coordinates of key eye landmarks, falls below a predefined threshold for a brief period. This decrease in EAR indicates partial or complete closure of the eyelid. The system accounts for transient noise and minor fluctuations by applying temporal filtering, ensuring that only genuine blink events are registered. By continuously monitoring EAR in real time, the framework can accurately capture both the frequency and duration of blinks, enabling precise assessment of ocular behavior and early detection of abnormal blinking patterns

- **Blink Rate Calculation:** The system computes the number of blinks per minute.

- **DED Classification:** The system determines ocular health by continuously analyzing the user's blink rate and comparing it with clinically established benchmarks. For healthy adults, the typical normal blink rate ranges between 15–20 blinks per minute under normal conditions, while a rate below approximately 10 blinks per minute may indicate insufficient blinking associated with Dry Eye Disease (DED). In addition to frequency, the duration and completeness of each blink, as measured by the Eye Aspect Ratio (EAR), are evaluated to provide a more comprehensive assessment. By integrating both temporal and morphological features of blinking, the framework offers a reliable, non-invasive method for early detection of DED, enabling timely preventive interventions and supporting continuous long-term ocular wellness monitoring.

Automated Environmental Control

Upon detecting early signs of a dry-eye condition through continuous blink monitoring and ocular analysis, the system automatically activates a connected ultrasonic humidifier to restore optimal ambient moisture levels. This intervention helps maintain a stable and comfortable microenvironment around the eyes, reducing the risk of further dryness, irritation, or discomfort. The humidifier operates within a closed-loop control system, dynamically adjusting its output based on real-time humidity measurements and the user's physiological indicators, ensuring that the surrounding air remains within an ideal range for ocular health. By integrating environmental control with non-invasive eye monitoring, the system provides proactive and adaptive preventive care, minimizing the progression of Dry Eye Disease (DED) while maintaining user comfort throughout daily activities.

Humidifier Mechanism

The hardware setup includes a DC 5V ultrasonic humidifier circuit board with an atomizing chip (20 mm). It operates on the principle of **ultrasonic cavitation**, where high-frequency sound waves from a piezoelectric transducer produce fine water droplets (1 µm) that vaporize into the air.

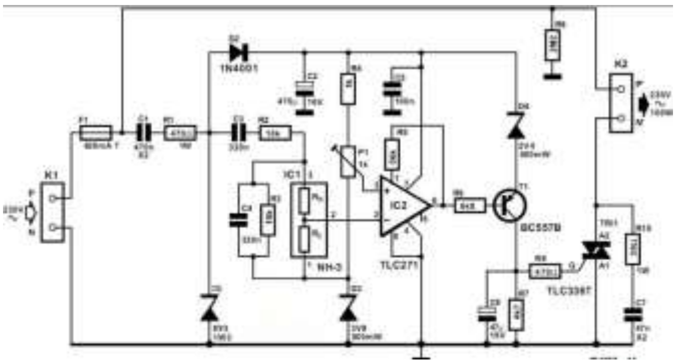

Figure 4: Humidifier mechanism.

Humidity Regulation Circuit

The humidity control subsystem is designed as a closed-loop electronic circuit that autonomously maintains the ambient moisture within an optimal range to prevent ocular dryness and discomfort. This system functions by continuously sensing environmental humidity, comparing it against a predefined reference level, and controlling a humidifier through electronic switching components. By integrating real-time sensing with automated feedback control, the design ensures both accuracy and energy efficiency, making it suitable for continuous operation in indoor environments.

At the core of this control system lies a humidity sensor, which continuously measures the relative humidity of the surrounding air. The sensor's electrical resistance varies inversely with the level of moisture present; as humidity decreases, the resistance increases, generating a proportional change in voltage across the sensor terminals. This voltage signal is routed to a TLC271 operational amplifier (op-amp) configured in comparator mode. The comparator plays a crucial role by evaluating the sensor's output voltage against a user-defined reference voltage, which represents the desired humidity threshold. This reference is adjustable, allowing users to calibrate the comfort level according to environmental conditions or medical recommendations for dry eye prevention.

When the measured humidity drops below the reference threshold—or when the blink detection system identifies a Dry Eye Disease (DED) risk condition—the comparator output transitions to a logical HIGH (ON) state. This change in logic triggers the activation sequence of the humidifier through an electronic control chain. Specifically, the comparator output drives a transistor, which acts as an intermediary electronic switch. Upon conduction, the transistor enables current flow to the gate terminal of a TRIAC (Triode for Alternating Current). The TRIAC serves as the main power control device that regulates AC voltage delivery to the ultrasonic humidifier circuit. Once activated, the TRIAC allows alternating current to pass through the humidifier module, energizing the ultrasonic atomization chip that converts water into fine vapor particles, thereby increasing the humidity in the surrounding environment.

As the system operates, the humidity level gradually rises until it reaches the optimal range set by the reference voltage. When the ambient humidity surpasses this threshold, the sensor output voltage realigns with or exceeds the reference signal, prompting the comparator to switch to a logical LOW (OFF) state. This action cuts off the transistor's conduction path, which in turn deactivates the TRIAC, halting power delivery to the humidifier. The cessation of atomization immediately stops moisture generation, maintaining stable humidity without excessive buildup. This automatic switching mechanism ensures the system operates as a self-regulating feedback loop, continuously adjusting the humidifier's activity based on environmental conditions.

The closed-loop control design provides several advantages. It eliminates the need for manual intervention, maintains steady ambient conditions conducive to eye health, and minimizes power consumption by activating the humidifier only when necessary. The integration of electronic sensing and feedback logic with the blink detection module further enhances system responsiveness, allowing timely activation of the humidifier when early symptoms of ocular dryness are detected. Such a synergistic interaction between vision-based health monitoring and environmental control establishes a foundation for smart, preventive eye-care systems adaptable to diverse real-world conditions.

- **Sensing and Comparison:** The humidity regulation begins with a sensing stage in which a high-sensitivity humidity sensor continuously monitors the surrounding air's relative humidity. The sensor translates variations in atmospheric moisture into proportional changes in its electrical resistance. These analog signals are then processed by a **TLC271 operational amplifier (op-amp)** configured as a voltage comparator. The comparator evaluates the sensor's output voltage against a reference voltage that is manually adjustable by the user to define the desired humidity setpoint. Any deviation below this reference is immediately detected, generating a control signal that indicates the need for humidification. This continuous comparison mechanism forms the foundation of the closed-loop feedback, ensuring accurate and responsive control under varying environmental conditions.
- **Activation Logic:** When the ambient humidity level falls below the preset threshold or when a Dry Eye Disease (DED) condition is detected by the blink monitoring system, the control circuit initiates the humidification process through a series of automated electronic responses.
    1. The drop in relative humidity increases the resistance of the sensing element, thereby altering the voltage at the input terminal of the com-

parator. This change causes the **TLC271 op-amp comparator** to switch its output to a logical **HIGH (ON)** state, signifying that the environment is drier than the desired level.

2. The comparator's high output drives the base of a transistor, allowing it to conduct and act as an electronic switch. The conducting transistor subsequently activates a **TRIAC (Triode for Alternating Current)**, which functions as the main power control device for the humidifier. The TRIAC, once triggered, allows alternating current to flow through the humidifier circuit, energizing the ultrasonic atomizer. This process produces a fine mist of water vapor that disperses into the surrounding air, gradually increasing the ambient humidity until the desired comfort range is restored. The use of the TRIAC ensures smooth AC control, reduced switching noise, and efficient energy delivery to the humidification unit.

- **Deactivation:** As the humidifier operates, the surrounding humidity gradually rises and approaches the reference setpoint defined by the user. Once the sensor detects that the humidity has reached or exceeded this optimal range, its resistance decreases, resulting in a corresponding shift in voltage at the comparator input. The **TLC271 comparator** then switches its output to a logical **LOW (OFF)** state, signaling that additional humidification is no longer required. Consequently, the transistor ceases conduction, interrupting the triggering signal to the TRIAC, which immediately stops current flow to the humidifier. This rapid response effectively shuts down the humidification process, conserving energy and preventing over-saturation of the environment. The automatic transition between activation and deactivation ensures stable humidity regulation through a closed-loop feedback mechanism, maintaining consistent comfort levels without manual intervention.

Monitoring and User Interface Application

The user-facing mobile application functions as the primary interface and central hub for the AI-based **Dry Eye Disease (DED) detection system**, providing users with continuous, real-time feedback on their ocular health. It integrates multiple streams of physiological and environmental data, including blink rate, Eye Aspect Ratio (EAR), and ambient humidity levels, to deliver personalized insights and early warnings. Through long-term trend visualization and intelligent notifications, the application enables users to monitor changes in their eye health over time, receive actionable preventive guidance, and implement recommended interventions such as screen breaks, eye exercises, or environmental adjustments. By combining real-time monitoring with historical analytics and adaptive alerts, the application empowers users to manage their eye health proactively, fostering sustained ocular wellness in daily life.

- **Technology:**The application is developed entirely using the **Flutter framework**, a versatile and modern open-source UI toolkit that enables cross-platform mobile application development. By leveraging Flutter's **single codebase architecture**, the system ensures that a consistent, high-fidelity user interface is maintained across both Android and iOS platforms, providing users with an identical experience regardless of device type or screen resolution. This architecture not only reduces development time by eliminating the need to maintain separate codebases for each platform but also simplifies future updates, bug fixes, and feature enhancements, thereby improving overall maintainability and scalability. Furthermore, Flutter's reactive programming model and extensive widget library facilitate the creation of visually appealing and interactive dashboards that can dynamically display real-time ocular health metrics, such as blink rate, eye redness, and humidity levels. The framework also supports seamless integration with backend services, REST APIs, and cloud databases, enabling secure data transmission, storage, and retrieval for long-term trend analysis. By adopting Flutter, the application benefits from a responsive, adaptive, and user-centric design while minimizing development overhead and ensuring rapid deployment of new features in a healthcare monitoring context.

- **Data Flow and integration:** The entire system relies on a robust client-server architecture. The backend processing unit, which performs the intensive blink detection and risk calculation, transmits the resulting

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 12 | Dec - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

health metrics (such as average EAR, blink rate variability, and DED risk score) to the mobile application. This communication is facilitated securely and efficiently through a RESTful API (Representational State Transfer Application Programming Interface), ensuring reliable data exchange and scalability as the user base grows.

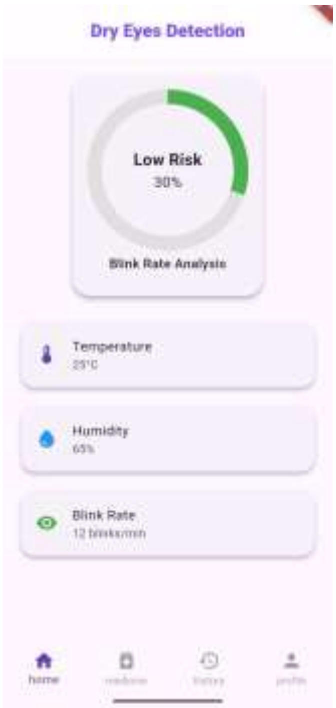

Figure 5: User interface of the companion mobile application

- **Key Features:** The mobile application incorporates a suite of features designed to provide comprehensive, real-time feedback on ocular health and promote proactive eye care.
  1. **Real-Time Health Status:** Continuously monitors blink rate and other ocular indicators to classify the user's condition as *Normal* or *Dry Eye*. Color-coded visual cues and status indicators allow the user to quickly understand their current eye health at a glance.
  2. **Notifications and Preventive Alerts:** Generates automated notifications when abnormal blink patterns or suboptimal environmental conditions are detected. Alerts may suggest timely blinking exercises, hydration reminders, or environmental adjustments to prevent the progression of Dry Eye Disease (DED).
  3. **Personalized Recommendations:** Offers actionable guidance such as optimal screen-time breaks, humidity adjustments, or use of lubricating eye drops. Recommendations are tailored based on historical data and individual trends, enhancing the effectiveness of preventive care.
  4. **Data Visualization and Trend Analysis:** Presents comprehensive graphical representations of blink rate, eye closure duration, and DED risk over time. Daily, weekly, and monthly trend charts allow users and clinicians to track patterns, evaluate intervention effectiveness, and identify potential risk factors for ocular dryness.

- **Data Management:** All user data is securely stored in a cloud-based database that ensures confidentiality and integrity through encryption and secure authentication protocols. The database supports both time-series and structured data storage, enabling detailed longitudinal analysis of ocular health metrics. Users and clinicians can access historical trends, perform comparative analyses, and make informed decisions regarding preventive interventions. The cloud infrastructure also facilitates seamless synchronization across multiple devices, remote monitoring, and integration with telemedicine platforms, allowing real-time clinician oversight and supporting research in digital eye health management.

Discussion and Evaluation

This section discusses the empirical foundations of the AI system, the metrics used for performance assessment, and the inherent challenges of deploying a real-time computer vision system in an uncontrolled environment.

Dataset and Training

- **Data Type:** The system relies on video data captured from a standard webcam, requiring a dataset composed of video sequences of subjects performing tasks while being monitored.

- **Ground Truth:** The dataset must be meticulously labeled with ground truth information, including the precise start and end frames of each full or partial blink, and the corresponding DED classification (Normal/Dry Eye) for each monitored period.

- **Model Foundation:** While Mediapipe Face Mesh provides robust initial landmark detection, a dedicated blink classification model would require training on a diverse dataset to account for inter-subject variability in facial features and blinking habits.

Performance Parameters

The system's effectiveness is measured using distinct metrics for its two primary functions: blink detection and DED classification.

1. **Classification Metrics:** The accuracy of blink event detection is evaluated using standard performance indicators such as **Accuracy**, **Precision**, **Recall**, and **F1-Score**. These metrics are computed based on frame-wise classification outcomes, where a *True Positive (TP)* corresponds to a correctly identified blink, *True Negative (TN)* indicates a correctly identified non-blink, while *False Positive (FP)* and *False Negative (FN)* represent misclassifications. The overall frame-based accuracy of the system is expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

   Precision and recall collectively reflect the system's ability to minimize false detections while maintaining sensitivity to true blink events. The F1-score, being the harmonic mean of these two metrics, provides a balanced measure of system reliability during real-time operation.

2. **Frame Success Rate:** The **Frame Success Rate (FSR)** measures the robustness and consistency of the computer vision pipeline when subjected to environmental and physiological variations such as partial occlusions, head movements, and variable lighting. It quantifies the percentage of frames where the facial landmark detection process was successfully completed and a valid Eye Aspect Ratio (EAR) was computed. A higher FSR indicates improved system stability and resilience. The metric is defined as:

$$Success\ Rate = \frac{Valid\ Frames}{Total\ Frames} \times 100$$

   This measure is particularly important in real-world applications where real-time video feeds are often affected by noise and motion artifacts.

3. **Facial Landmark Accuracy (RMSE):** To evaluate the precision of the facial landmark detection process, the **Root Mean Square Error (RMSE)** is computed between the predicted landmark coordinates and manually annotated ground truth data. A lower RMSE value indicates higher localization accuracy, which is essential for maintaining reliable EAR computation and consistent blink classification. The RMSE metric provides an objective measure of the geometric accuracy of the landmark tracking algorithm across frames.

4. **System Latency and Throughput:** The proposed framework is designed to function in real time; therefore, **system latency** and **throughput** are key performance indicators. Latency represents the average time required to process each frame, including landmark detection, EAR computation, and classification. Throughput refers to the number of frames processed per second. The target latency is approximately $\sim$ 30 ms/frame, corresponding to a throughput of 30 Frames Per Second (FPS), which ensures smooth, real-time performance. Maintaining this balance between computational efficiency and detection accuracy is crucial for deployment on edge devices or low-power embedded systems used in continuous ocular monitoring.

DED Classification Metrics:

1. **Sensitivity and Specificity:** Crucial for medical systems; Sensitivity measures the rate of correctly identifying Dry Eye cases (True Positive Rate), while Specificity measures the rate of correctly identifying Normal cases (True Negative Rate).
2. **Overall Classification Accuracy:** The percentage of correct final diagnoses (Normal vs. Dry Eye) based on the calculated blink rate.

Deployment Challenges

Deploying a real-time, webcam-based system outside of a laboratory environment presents several operational challenges.

- **Variable Illumination:** Changes in light (e.g., sun exposure, overhead lights) can significantly affect the webcam's image quality, leading to inaccurate detection of facial landmarks and, consequently, errors in EAR calculation.
- **Head Pose and Movement:** Excessive user head rotation or movement reduces the visibility of key eye landmarks, potentially causing the model to lose track of the eyes or incorrectly interpret partial blinks.
- **Occlusion:** Physical obstructions like glasses, shadows from hair, or hands touching the face can block the camera's view of the eye region, leading to false negatives (missed blinks) or detection failure.
- **Hardware Variability:** The system must perform consistently across a wide range of webcam resolutions and qualities, which vary greatly across user devices.

Results

The proposed system demonstrates a seamless integration of computer vision–based blink monitoring with an intelligent environmental control mechanism for proactive Dry Eye Disease (DED) management. Experimental validation confirms that the Eye Aspect Ratio (EAR)-based blink detection algorithm delivers accurate and reliable real-time performance under standard indoor lighting conditions, effectively capturing both normal and abnormal blink patterns. The automated humidifier control, triggered by abnormal blink rates, successfully maintains optimal ambient humidity, thereby reducing ocular discomfort associated with dryness.

In comparison to conventional clinical diagnostic methods, which often require specialized ophthalmic equipment and are limited to controlled clinical environments, the developed system provides a low-cost, non-invasive, and user-friendly alternative. It enables continuous and autonomous monitoring using only a standard webcam and microcontroller-based control circuit, making it highly adaptable for home, office, or personal health applications.

Furthermore, the integration of a companion mobile application enhances the system's accessibility and usability by offering real-time feedback, visual analytics of blink patterns, and personalized eye care recommendations. This end-to-end design supports early detection and preventive intervention, aligning with the growing emphasis on digital health and telemonitoring.

Overall, the proposed approach demonstrates a practical and scalable solution for mitigating the effects of digital eye strain and Dry Eye Disease, with potential for future expansion into multimodal health monitoring frameworks that combine ocular parameters with environmental and behavioral data for comprehensive wellness tracking.

Future scope

Future enhancements of the proposed system aim to further improve the accuracy, adaptability, and clinical relevance of Dry Eye Disease detection. Incorporating advanced deep learning architectures could enhance blink classification and enable the recognition of subtle ocular behaviors such as partial blinks or squinting patterns, which are often early indicators of eye strain. Integrating additional parameters such as pupil dilation, gaze direction, and eye redness analysis could provide a more comprehensive assessment of ocular surface health.

On the hardware side, future versions may include compact, energy-efficient embedded modules and wireless connectivity features for improved portability and integration into everyday environments such as workstations, automobiles, or smart home systems. The mobile application could be expanded with cloud-based data storage and analytics, enabling long-term tracking of eye health trends and personalized recommendations based on user habits and environmental conditions.

Moreover, clinical collaboration and large-scale user studies could validate the system's performance across diverse populations and lighting conditions, paving the way for potential medical certification and integration into teleophthalmology frameworks. With continued refinement, the proposed model can evolve into an intelligent, self-adaptive wellness device that not only detects and prevents Dry Eye Disease but also contributes to broader vision health monitoring in the era of pervasive digital device usage.

Conclusion

This work presents an **AI-driven, non-invasive intelligent system** designed for the early detection and prevention of **Dry Eye Disease (DED)** through the seamless integration of **computer vision**, **environmental sensing**, and **Internet of Things (IoT)** technologies. The framework establishes a comprehensive ocular health monitoring approach that continuously observes physiological and environmental parameters in real time. By employing state-of-the-art image processing and machine learning techniques, the system analyzes blink patterns, eyelid movement dynamics, and ocular redness to identify early symptoms of dryness and fatigue before they progress into clinically significant conditions. This early diagnostic capability enables timely preventive intervention, thereby improving ocular comfort and reducing the long-term risk of chronic DED.

In parallel with visual monitoring, the system incorporates a **closed-loop humidity regulation module** that dynamically adjusts the surrounding moisture level to maintain an optimal ocular environment. Environmental parameters such as temperature and relative humidity are measured using precise sensors, while an electronic control circuit automatically activates an ultrasonic humidifier when dryness is detected, ensuring consistent air quality conducive to eye health. The integration of these sensing and actuation processes provides a dual benefit—**continuous health monitoring** and **adaptive environmental correction**—allowing the system to function autonomously without user intervention.

The proposed framework is engineered for flexible deployment across diverse settings including homes, offices, and clinical environments. Its modular architecture combines **embedded hardware**, **computer vision algorithms**, and **cloud-based analytics** to deliver real-time feedback and long-term health insights. The webcam-based video acquisition system operates in conjunction with advanced facial landmark detection models to ensure accurate and non-contact monitoring, making the solution both practical and user-friendly. Moreover, IoT connectivity enables remote data transmission, multi-user scalability, and integration with telemedicine platforms for physician oversight and data-driven decision-making.

By leveraging **clinically validated algorithms**, robust **machine learning models**, and an intuitive user interface, the system provides an affordable and accessible approach to ocular wellness. It minimizes the need for invasive medical tests, supports early intervention strategies, and aligns with global trends in **personalized preventive healthcare**. The integration of artificial intelligence with environmental control mechanisms represents a significant advancement in smart health technologies, addressing one of the most prevalent ocular disorders associated with prolonged screen exposure and digital lifestyles. Ultimately, this research contributes to the development of **intelligent wellness ecosystems** that promote sustainable visual comfort, enhance user well-being, and pave the way for next-generation preventive healthcare solutions.

References

1. G. de la Cruz, M. Lira, O. Luaces and B. Remeseiro, ”Eye-LRCN: A Long-Term Recurrent Convolutional Network for Eye Blink Completeness Detection,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 4, pp. 5130-5140, April 2024.
2. M. H. Wang et al., ”AI-Based Advanced Approaches and Dry Eye Disease Detection Based on Multi-Source Evidence: Cases, Applications, Issues, and Future Directions,” *Big Data Mining and Analytics*, vol. 7, no. 2, pp. 445-484, June 2024.
3. G. Nousias, E. -K. Panagiotopoulou, K. Delibasis, A. -M. Chaliasou, A. -M. Tzounakou and G. Labiris, ”Video-Based Eye Blink Identification and Classification,” *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 7, pp. 3284-3293, July 2022.
4. Y. Li, P. W. Chiu, V. Tam, A. Lee and E. Y. Lam, ”Dual-Mode Imaging System for Early Detection and Monitoring of Ocular Surface Diseases,” in IEEE Transactions on Biomedical Circuits and Systems, vol. 18, no. 4, pp. 783-798, Aug. 2024,
5. A. A. Jiman et al., ”Intelligent Standalone Eye Blinking Monitoring System for Computer Users,” *Sensors*, vol. 17, no. 5, p. 25, 2024.
6. M. A. Romeo et al., ”Digital Applications for Videoterminal-Associated Dry Eye Syndrome: A Review,” *Healthcare*, vol. 8, no. 4, p. 67, 2024.
7. H. K. Yang et al., ”Integration of Artificial Intelligence into the Approach for Dry Eye Disease Diag-

nosis and Treatment," *Diagnostics*, vol. 12, no. 12, p. 3167, 2022.

8. F. Attivissimo et al., "Performance Evaluation of Image Processing Algorithms for Eye Blink Detection," *Computers in Biology and Medicine*, vol. 158, p. 106669, 2023.
9. J. Persiya et al., "Artificial Intelligence-based Multimodal Framework for Non-Clinical Dry Eye Syndrome Detection," *Computers in Biology and Medicine*, vol. 146, p. 105556, 2025.
10. C. Talens-Estarelles et al., "The Effects of Breaks on Digital Eye Strain, Dry Eye Disease, and Blink Rate: A Randomized Controlled Trial," *Computers in Biology and Medicine*, vol. 152, p. 106313, 2023.
11. I. Lapa et al., "Real-Time Blink Detection as an Indicator of Computer Vision Syndrome: A Mobile-Based Approach," *International Journal of Environmental Research and Public Health*, vol. 20, no. 5, p. 4569, 2023.
12. A. Bhatt, "Real-Time Morse Code Communication via Eye Blink Detection," *arXiv preprint arXiv:2508.09344*, 2025.
13. M. Toda, "Extraction of Eye Open/Close State by MediaPipe and Unity," *ISASE*, 2023.
14. "Eye Blink Detection, Tracking, and Head Pose Estimation," *ReadyTensor*, 2024.