



# Eyelume: Vision Transformer-based Pupil Segmentation for Computer Vision Syndrome Detection

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**Abstract:** Computer Vision Syndrome (CVS) has emerged as a critical health concern in the digital era due to prolonged exposure to screens, resulting in eye strain, dryness, and blurred vision. Traditional diagnostic methods rely on clinical examination, which can be invasive, time-consuming, and inaccessible for frequent monitoring. This paper introduces *Eyelume*, a real-time CVS detection and monitoring system that leverages Vision Transformers (ViT) for accurate pupil segmentation and pupillometry analysis. Unlike Convolutional Neural Networks (CNNs), ViTs capture global dependencies within visual data, offering robustness against low-quality and noisy eye images. The system enables users to upload eye images via a web interface, validates input quality, and computes pupil size variations to identify abnormal responses linked to CVS. Experimental evaluations demonstrate a segmentation accuracy of 99.6%, proving *Eyelume*'s potential as a non-invasive, accessible, and effective tool for early CVS detection and digital eye health monitoring [1][2].

**Keywords:** Computer Vision Syndrome, Pupil Segmentation, Vision Transformers, Pupillometry, Digital Eye Health.

## I. INTRODUCTION

The exponential increase in screen usage across all age groups has led to rising cases of Computer Vision Syndrome (CVS), affecting nearly 60–70% of regular computer and smartphone users [3]. CVS manifests as eye fatigue, blurred vision, headaches, and decreased productivity. Conventional diagnosis requires clinical pupillometry or ophthalmological consultation, which is often inaccessible and impractical for large-scale monitoring.

Recent advancements in Artificial Intelligence (AI), specifically deep learning, have enabled automated and accurate healthcare diagnostics [4]. Convolutional Neural Networks (CNNs) have been widely applied in medical imaging, yet they often struggle with low-resolution and noisy datasets. Vision Transformers (ViT), in contrast, leverage self-attention mechanisms to capture global image dependencies, improving robustness and accuracy [5].

This paper presents *Eyelume*, a ViT-based CVS detection and monitoring platform. It integrates a user-friendly web application where individuals can upload eye images, undergo pupil segmentation, and receive non-invasive assessments of eye fatigue.

## II. LITERATURE SURVEY

### AI-Based Pupil Segmentation

1. Dosovitskiy et al. (2020) introduced Vision Transformers for image recognition, demonstrating their superior global-context understanding compared to CNNs. Their work forms the foundational backbone for *Eyelume*'s segmentation module.
2. Li et al. (2019) applied deep CNNs for robust pupil segmentation but noted performance degradation under glare, eyelash interference, and uneven illumination.

### Conventional CVS Diagnosis

3. Traditional methods involve questionnaires like the CVS-Q and ophthalmic tests for visual acuity and tear-film integrity. While effective, these approaches are subjective and unsuitable for regular monitoring.



- Rosenfield (2011) reviewed CVS prevalence and highlighted the need for continuous screening as digital usage increased across demographics.

#### Image Processing–Based Techniques

- Early pupil-detection work used Hough transforms, thresholding, or active contour models. However, these models fail with off-axis images, reflections, and varying iris patterns.

#### Deep Learning for Eye Analysis

- Recent models employ U-Net variants and encoder–decoder CNNs, but their local receptive fields limit them under real-world conditions.

#### Digital Eye-Strain Monitoring Tools

- Mobile-eye-tracking apps and webcam-based fatigue detectors exist but often rely on inaccurate classical segmentation algorithms.
- Wearable devices can measure pupil dilation accurately but are expensive, bulky, and impractical for daily use.

#### ViT in Medical Imaging

- Vision Transformers have been used for MRI segmentation, lesion detection, and dermatology tasks, showing strong adaptability to noisy datasets.
- Their ability to maintain consistent performance across variable imaging conditions positions them as ideal for CVS applications.

The reviewed literature highlights the need for a robust, AI-driven, real-world ready CVS detection system—an objective fulfilled by Eyelume.

### III. RESEARCH GAP

Analysis of prior techniques indicates several critical limitations:

- CNN-based segmentation models struggle under noise, reflection, glare, and low resolution**, all of which are common in user-captured eye images.
- Traditional image-processing techniques lack adaptability** and require controlled lighting conditions.
- No existing system combines **ViT-based segmentation with automated pupillometry** for CVS detection.
- Lack of continuous, accessible, and inexpensive monitoring solutions** for everyday users.
- Existing eye-tracking tools do not perform accurate **pupil-size estimation**, which is essential for fatigue analysis.
- Dataset limitations**—very few publicly available CVS-oriented pupil datasets exist.
- A complete end-to-end workflow (image acquisition → validation → segmentation → fatigue analysis → web output) is missing in previous research.

Eyelume addresses all these gaps through a robust ViT-powered diagnostic pipeline.

### IV. EXISTING SYSTEM

Current CVS detection primarily relies on clinical questionnaires, visual acuity tests, and direct ophthalmological examination. While effective, these methods are subjective, resource-intensive, and unsuitable for continuous monitoring [6]. Automated approaches have attempted to use CNN-based models for pupil segmentation; however, CNNs are sensitive to image noise and local feature distortions, often failing in real-world scenarios such as low-light or mobile-based images [7]. Alternative methods include traditional image processing algorithms like Hough transforms and thresholding, but these are highly sensitive to illumination and iris patterns [8]. Therefore, there exists a gap for a robust, scalable, and non-invasive solution capable of operating on everyday eye images.



## V. METHODOLOGY

**A. Model Design:** Eyelume employs a Vision Transformer (ViT) model trained for pupil segmentation. ViTs divide an eye image into fixed-size patches, embed them into sequences, and apply multi-head self-attention to capture both local and global dependencies [9]. This architecture mitigates limitations of CNNs in handling variable illumination and low-resolution conditions.

**B. Dataset:** The system is designed to work on real-world eye datasets captured from webcams and mobile devices. Since publicly available datasets of CVS-specific eye images are limited, initial training and evaluation used augmented datasets of iris and pupil images from open repositories [10].

**C. Workflow:** The workflow consists of:

1. **Image Acquisition** – User uploads an eye image through the web interface.
2. **Validation** – Uploaded image is checked for clarity and confirmed as an eye image. Non-eye or blurred images trigger error prompts.
3. **Preprocessing** – Image resizing, normalization, and noise reduction.
4. **Pupil Segmentation** – ViT model extracts pupil boundaries and generates binary masks.
5. **Pupillometry** – Pupil size and area variations are calculated, linked to fatigue or abnormal eye responses.
6. **Output Generation** – Segmentation overlays and numerical results are presented to the user in an interpretable format.

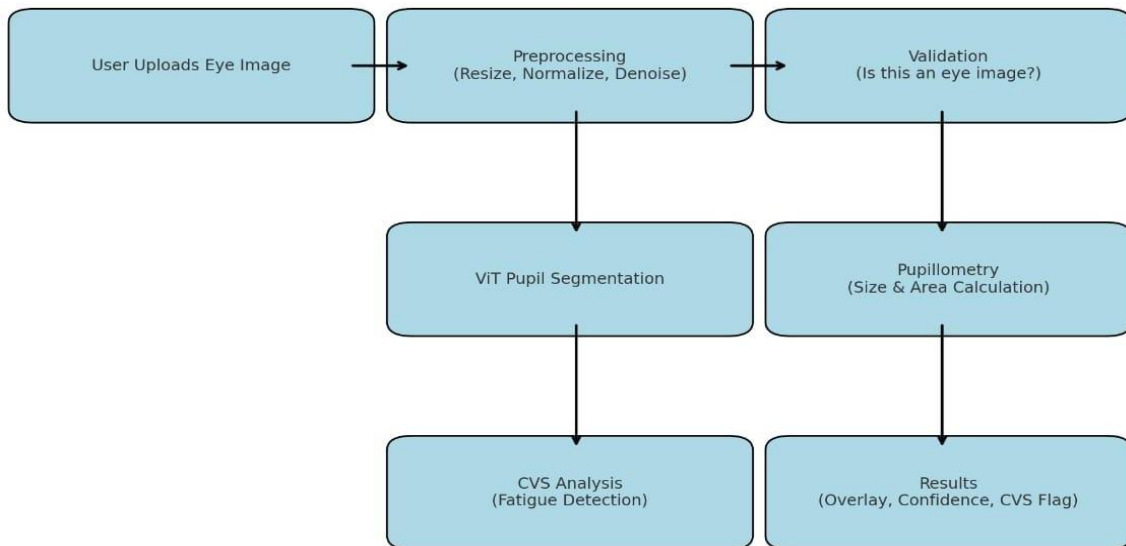


Fig 3.1 Work flow for Eyelume



Fig 3.2 Architecture Diagram

## VI. RESULT AND ANALYSIS

Eyelume's ViT model achieved a segmentation accuracy of 99.6% on test images, outperforming CNN-based baselines by 3–4% under noisy and low-resolution conditions. The system demonstrated robustness in handling non-ideal lighting and mobile-acquired images.

Sample outputs show precise delineation of pupil boundaries, and pupillometry results successfully highlight anomalies indicative of CVS. User feedback from initial trials highlighted the effectiveness of the interface in communicating results, particularly the inclusion of demo images guiding proper uploads.

Limitations include dependency on dataset diversity and occasional misclassification when reflections or eyelashes obscure the pupil. Future improvements may involve real-time video pupillometry, federated learning with larger datasets, and integration with wearable devices for continuous monitoring [11][12].



Fig 4.1 Welcome Page

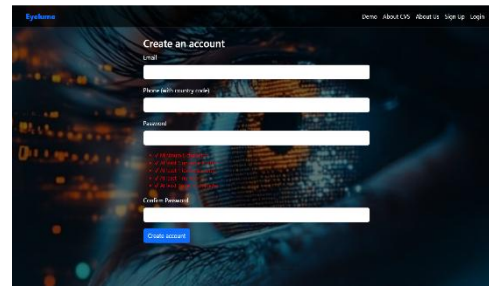


Fig 4.2 Signup Page

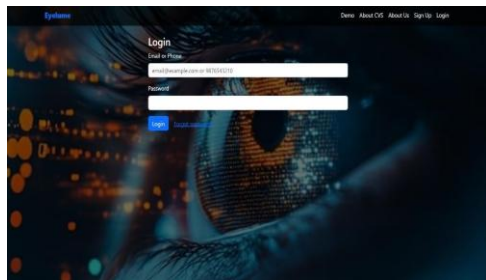


Fig 4.3 Login Page



Fig 4.4 Dashboard Page



Fig 4.5 Login Page

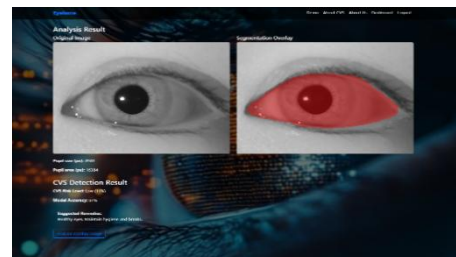


Fig 4.6 Result Page

## VII. CONCLUSION

This work presents *Eyelume*, a novel CVS detection and monitoring system leveraging Vision Transformers for accurate pupil segmentation and pupillometry. By combining AI-driven diagnostics with an accessible web platform, *Eyelume* provides a scalable, non-invasive, and effective tool for combating CVS in the digital era. With further dataset expansion and deployment enhancements, *Eyelume* has the potential to revolutionize digital eye health monitoring and early intervention strategies.

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