# Cognitive Load Estimation from Eye Gaze & Micro-Expressions in Remote Work/Learning

A Machine Vision Approach to Enhance Digital Well-being

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# Abstract

The shift to prolonged screen time in remote work and education presents a significant challenge in managing cognitive fatigue. Our project addresses this by developing a system to estimate an individual's cognitive load in real-time using only a standard webcam. Leveraging Python libraries like OpenCV and MediaPipe, the system tracks key physiological indicators such as blink rate, pupil dilation, and micro-expressions related to concentration. This data is processed by a machine learning model to compute a normalized "Strain Index" on a 0-100 scale. The output is visualized on a real-time dashboard that triggers actionable alerts when sustained strain is detected. Our objective is to provide an accessible tool that empowers users to better manage their cognitive workload and foster healthier screen-time habits.

# Literature Survey

## 1. Using Gaze Behavior to Measure Cognitive Load (Perkhofer & Lehner, 2018)

- Objective: This paper provides a comprehensive overview of how different eye-tracking metrics serve as reliable indicators of cognitive load.
- Key Findings:
  - It confirms a strong correlation between mental effort and specific gaze behaviors.
  - Pupil Dilation: Directly linked to task difficulty; as a task gets harder, pupil size increases.
  - Fixation Duration: Longer fixations are observed when individuals are processing complex information.
  - Saccade Patterns: The velocity and frequency of saccades (rapid eye movements) change under high cognitive strain.
- Contribution: This work establishes the scientific foundation for using non-invasive eye-tracking as a valid and objective proxy for measuring a person's cognitive state, moving beyond subjective self-reports.
- Takeaway: The core principle of our project—that eye movements reveal mental effort—is strongly supported in the literature.

# Literature Survey

## 2. "Eye tracking cognitive load using pupil diameter and microsaccades with fixed gaze" (Krejtz et al., 2018)

- **Objective:** To test if pupil diameter and microsaccades (tiny, involuntary eye movements) are sensitive to cognitive load even when a user's primary gaze is fixed on one point.
- **Methodology:**
  - Participants performed an n-back task (a classic cognitive load test) with varying levels of difficulty (0-back, 1-back, 2-back).
  - The system measured pupil size and the rate of microsaccades.
- **Key Findings:**
  - Pupil diameter systematically increased with task difficulty.
  - The rate of microsaccades significantly *decreased* as cognitive load increased, suggesting mental effort inhibits these tiny movements.
- **Contribution:** This study proves that cognitive load can be reliably measured even in static viewing conditions, which is common during remote work (e.g., reading a document, watching a lecture).
- **Takeaway:** Our system can rely on subtle but powerful signals like pupil changes and microsaccade suppression, which are detectable with modern cameras.

# Literature Survey

## 3. "Your Eyes Tell: Leveraging Smooth Pursuit for Assessing Cognitive Workload" (Kosch et al., 2018)

- Objective: To explore a less common but valuable metric: the quality of "smooth pursuit" eye movements. Smooth pursuit is the act of smoothly tracking a moving object with the eyes.
- Hypothesis: The ability to smoothly track an object degrades as a person's cognitive load increases because fewer mental resources are available for the tracking task.
- Key Findings:
  - When participants performed a secondary task that increased cognitive load, their ability to smoothly follow a moving dot on screen worsened.
  - The error rate (how far the gaze deviates from the object) was a strong predictor of the current cognitive workload.
- Contribution: This research expands the set of potential eye-tracking features beyond simple fixations and saccades. It shows that the *quality* and *accuracy* of eye movements are also rich sources of information.
- Takeaway: A sophisticated cognitive load model can benefit from a diverse feature set, including the quality of different types of eye movements.

# Literature Survey

## 4. Cognitive workload level estimation based on eye tracking: A machine learning approach" (Skaramagkas et al., 2021)

- Objective: To design and validate a complete system that uses machine learning to classify different levels of cognitive workload based *only* on eye-tracking data.
- Methodology:
  - Extracted a wide range of features from an eye tracker: pupil diameter, blink statistics, saccade and fixation metrics.
  - Trained and tested several machine learning classifiers (Support Vector Machines, Random Forests, k-NN).
- Key Findings:
  - The machine learning models were able to classify three distinct levels of cognitive workload (low, medium, high) with high accuracy (over 90% in some cases).
  - Pupil-related features were consistently ranked among the most important predictors.
- Contribution: This paper provides a direct blueprint and validation for our project's core methodology: using a set of eye-gaze features to train a model that outputs a cognitive load score.
- Takeaway: Machine learning is a proven and highly effective method for turning raw eye-tracking data into an accurate cognitive load estimation.

# Literature Survey

**5. "Multimodal Cognitive Load Classification using Eye-tracking and Facial-expression data" (Gertych et al., 2021)**

- Objective: To determine if combining eye-tracking data with facial expression features improves the accuracy of cognitive load classification compared to using either modality alone.
- Key Findings:
  - Facial expressions, particularly around the eyes and brow (related to Action Units), changed significantly with cognitive load.
  - A "fusion model" that used both eye-gaze and facial features performed significantly better than models that only used one type of data.
- Contribution: This work scientifically validates the core hypothesis of our project—that combining eye-gaze analysis with facial micro-expression analysis creates a more robust and accurate system.

# Block Diagram

# References

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# THANK YOU