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NeuroEye: AI-Powered Eye Tracking for Mental Health Detection

Prof. Pooja Patle[1], Ms. Amisha Bhimte[2], Ms. Dhanashree Tembhare[3] Ms. Rakhi Shiwankar[4], Ms. Kunjal Yawalkar[5], Ms. Sneha Damale[6]

Assistant Professor, Computer Technology, Priyadarshini College of Engineering, Nagpur, India[1]

UG Student, Computer Technology, Priyadarshini College of Engineering, Nagpur, India[2]

UG Student, Computer Technology, Priyadarshini College of Engineering, Nagpur, India[3]

UG Student, Computer Technology, Priyadarshini College of Engineering, Nagpur, India[4]

UG Student, Computer Technology, Priyadarshini College of Engineering, Nagpur, India[5]

UG Student, Computer Technology, Priyadarshini College of Engineering, Nagpur, India[6]

Abstract: Mental health is one of the most neglected areas in healthcare systems around the world. Issues like depression, anxiety, ADHD, and chronic stress affect millions of people, yet a large number never get screened or diagnosed. One core reason is that most current detection approaches rely heavily on self- reported information, which is often unreliable when people feel too embarrassed, are in denial, or simply lack awareness of their own condition. To address this, we built NeuroEye — a browser-based tool that tracks eye activity passively during a session to detect early signs of mental distress. Instead of asking users to fill out questionnaires, NeuroEye uses a regular webcam to observe natural eye behaviour in the background. It uses the MediaPipe Face Mesh library to detect facial landmarks and calculate the Eye Aspect Ratio (EAR) for monitoring blinks in real time. Gaze tracking is done by monitoring iris position across nine zones. These signals are then compared against known clinical thresholds to identify possible indicators of stress, low mood, fatigue, or attention issues. All processing happens locally on the user's device and no data is sent to any server, keeping everything completely private. NeuroEye is a screening support tool and is not a replacement for professional diagnosis.

Keywords: Affective Computing, Eye Aspect Ratio (EAR), MediaPipe Face Mesh, Mental Health Screening, Ocular Biometrics, Gaze Estimation, Non-invasive Assessment

I. INTRODUCTION

Mental health continues to be treated as a lower priority in healthcare systems globally, even as the number of people dealing with such conditions keeps growing. Disorders like depression, anxiety, and attention-related issues tend to develop gradually and without obvious symptoms, making early detection very difficult — especially outside of a clinical setting. Several factors contribute to this: lack of affordable care, limited availability of services in rural or underserved areas, and the persistent social stigma attached to mental illness. The bigger challenge is that current screening tools mostly depend on self-reporting through questionnaires and structured interviews. While useful to some extent, these methods break down when people are not self-aware about their symptoms, or when they intentionally underreport how they are feeling to avoid being judged. Early detection becomes nearly impossible in such cases, even though early intervention has been shown to be the most effective. What is interesting is that decades of research in neuroscience and psychology have shown that eye activity is a strong reflection of mental state. Blink patterns, gaze movements, and fixation behaviour have all been linked to various neurological and psychological conditions — and unlike verbal self-reports, these are responses a person has little conscious control over. NeuroEye was designed around this insight. It is a browser-based application that uses a standard webcam to observe eye behaviour in real time without requiring any installation or account creation. All processing runs on the user's own device using MediaPipe's Face Mesh model, generating a session report that can be kept private or shared with a healthcare provider. The goal was to build something genuinely accessible — something that a student, a remote worker, or someone in a rural area with no access to mental health services could actually use without barriers.

Another important dimension of this problem is how people perceive mental health tools, especially younger individuals. Even when professional help is available, many people — particularly students and young adults —

hesitate to reach out due to fear of judgment, being labelled, or being misunderstood by others. This social and psychological barrier is just as significant as financial or geographic ones, and it results in a large number of people

who could genuinely benefit from early support never taking the first step. A passive tool that does not require the user to acknowledge or admit a problem openly has the potential to reach people who would otherwise never engage with any form of mental health support. It is also important to note that NeuroEye is not a continuous monitoring system. Each session is initiated by the user, runs independently, and all data stays under the user's control. This approach was deliberately chosen to align with growing concerns around data privacy and ethical design in digital health. Rather than collecting or storing data in any centralised way, NeuroEye keeps the user informed and in charge of all outcomes — supporting more responsible and autonomous personal health decisions.

II. LITERATURE REVIEW

Research connecting eye behaviour to psychological state has been building across neurology, psychiatry, and human-computer interaction for several decades. The following studies form the core literature that NeuroEye draws on:

Blink Rate as a Neurological Indicator: Early research by Karson (1983) established a clear link between spontaneous blink rate and dopamine activity in the brain, noting that neurological conditions such as Parkinson's disease and schizophrenia — both of which disrupt dopamine pathways — also cause measurable changes in blink frequency. This foundation was later extended to mental health contexts by Zaman and Choudhury (2021), who found that people experiencing depression or anxiety tend to blink at rates falling outside the typical adult range of 12 to 22 blinks per minute. Further evidence from Thibaut et al. (2020) on children with ADHD revealed that blink timing irregularities were equally informative as blink count, indicating that both the frequency and the consistency of blinking carry diagnostic significance.

Eye Aspect Ratio for Blink Detection: Soukupova and Cech (2016) introduced a geometry-based approach to blink detection by placing six landmark points around each eye and computing a ratio that reflects how open the eye is at any point in time. This ratio — the Eye Aspect Ratio (EAR) — drops noticeably during a blink and returns to its baseline value as the eye reopens. Their findings indicated that an EAR threshold of 0.2 reliably distinguishes blink events, and this value has since been adopted widely in eye-tracking research including our own implementation. Work by Drutarovsky and Fogelton (2014) further demonstrated that the EAR-based approach remains effective in real-world video conditions when combined with frame-level smoothing to reduce noise.

Facial Landmark Detection: Lugaresi et al. (2019) introduced the Face Mesh pipeline within MediaPipe, enabling real-time tracking of 468 facial landmarks using only a standard webcam — eliminating the need for any specialised hardware. This made it a practical foundation for a browser-based system like NeuroEye. Kartynnik et al. (2019) validated the accuracy of this pipeline, reporting average localization errors under 2mm in typical conditions, which is precise enough to support both EAR computation and iris-based gaze estimation. A subsequent update to the pipeline introduced iris-specific landmark tracking, enabling full gaze direction estimation within a browser environment — a capability that had previously required dedicated eye-tracking hardware.

Browser-Based Machine Learning: Smilkov et al. (2019) demonstrated that machine learning inference inside a browser environment was not only feasible but could run at speeds that make real-time applications practical. For NeuroEye, this was a foundational finding — it meant that the entire processing pipeline could execute on the user's own device without sending any biometric data to an external server. This client-side architecture directly resolves the privacy concerns that typically arise with digital health tools.

Research Gap: While each of the above areas — blink analysis, facial landmark detection, EAR computation, and browser-based ML — has been individually studied and validated, the integration of all these components into a single, accessible, privacy-first mental health screening tool has not been widely explored. A significant portion of existing work in this area focuses either on driver drowsiness detection or on clinical setups that require specialised equipment and controlled environments. NeuroEye attempts to fill this gap by bringing these techniques together in a way that is lightweight, installation-free, and usable by anyone with a webcam.

III. METHODOLOGY

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NeuroEye operates through a four-stage processing pipeline that begins with raw webcam input and produces structured mental health indicators, all running entirely within the user's browser with no server-side computation at any stage.

System Architecture: NeuroEye is implemented as a single-page web application built with HTML5, CSS3, and JavaScript. External libraries including MediaPipe Face Mesh and Chart.js are loaded via CDN links, removing any need for local installation. When a session starts, the browser captures the webcam stream and feeds each video frame into the Face Mesh model, which returns a set of 468 facial landmark coordinates. These coordinates are then used to compute blink and gaze measurements on every frame.

The computed metrics feed into a threshold-based inference engine that classifies mental state in real time, with results shown live on a session dashboard. At the end of the session, all collected data is compiled into a downloadable text report.

Data Collection and Signal Processing: Throughout a session, NeuroEye records three categories of data. Ocular data includes per-frame EAR values, iris position coordinates, timestamps of each blink event, and individual blink durations. Gaze data captures the normalised displacement of the iris across nine spatial zones — a central zone, four cardinal directions (up, down, left, right), and four diagonal directions. Session-level statistics are then derived, including blink rate in blinks per minute, the Coefficient of Variation (CV) of the intervals between blinks, and average blink duration across the session.

The EAR itself is calculated using six landmark points placed around each eye, using the formula below:

$$EAR = (\|p2 - p6\| + \|p3 - p5\|) / 2 \times \|p1 - p4\|$$

To reduce false blink detections caused by momentary frame-level noise, raw EAR values are smoothed using a three-frame rolling average before any blink is registered. A blink is confirmed only when the smoothed EAR value remains below 0.21 for a minimum of two consecutive frames. Gaze zone classification works by measuring how much the iris has moved away from the geometric centre of the eye region and mapping that displacement to the nearest of the nine defined zones.

Inference Engine and Classification Rules: The inference engine takes the per-session statistical metrics and maps them to potential mental health signals using the following rule set:

Stress / Anxiety: Blink rate above 25 per minute or CV greater than 0.50

Depression / Low Mood: Blink rate dropping below 10 per minute

Attention / ADHD Indicators: CV exceeding 0.65 while blink rate stays within the normal range

Eye Fatigue: Mean blink duration longer than 250 ms

Normal Range: Blink rate between 12 and 22 per minute with CV below 0.50

At the end of each session, the system produces a plain-text report containing all measured values, the primary mental state classification, a breakdown of gaze zone distribution across the session, and general wellness recommendations based on the detected patterns. Users can save this report to their device or share it with a healthcare professional for a more detailed follow-up evaluation.

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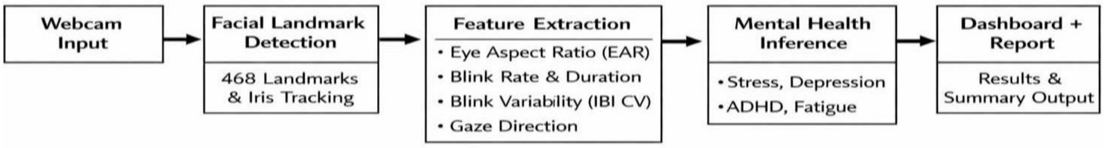
IV. BLOCK DIAGRAM



V. FLOWCHART

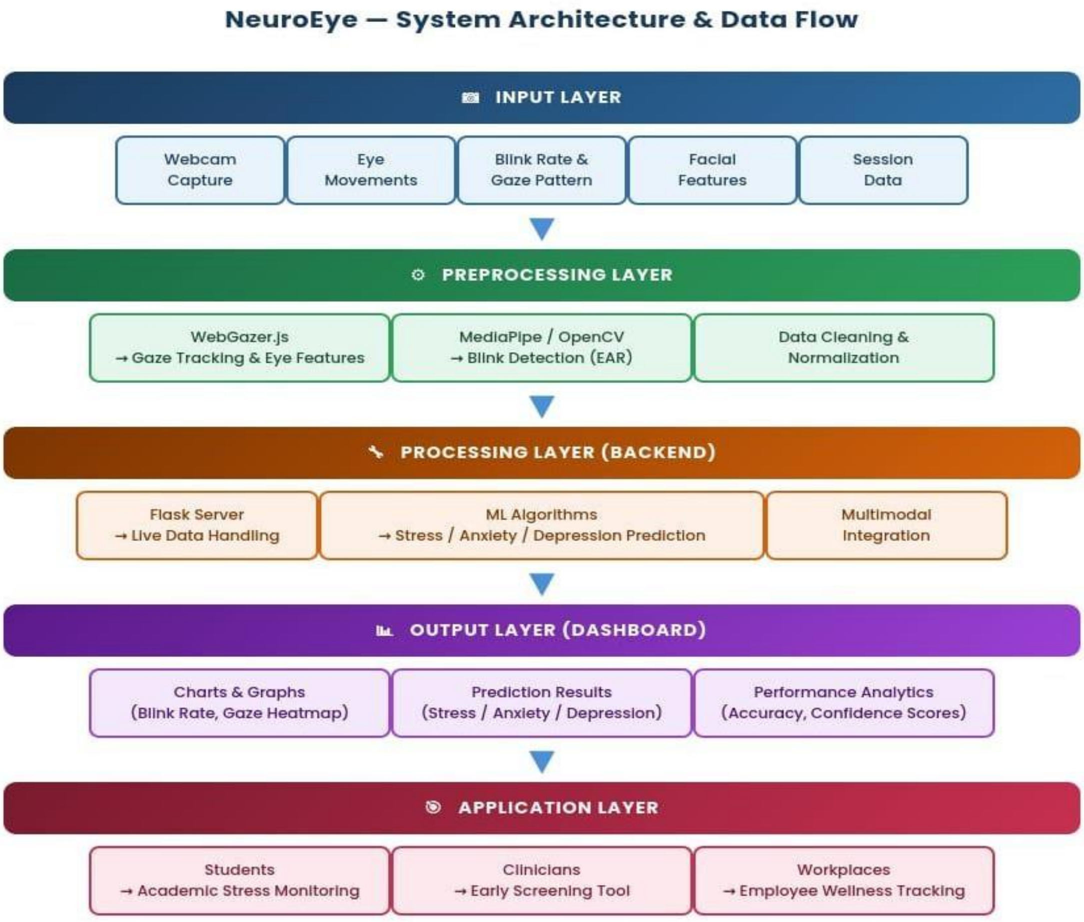


Figure 1: NeuroEye System Architecture and Data Flow

VI. RESULT & DISCUSSION

A. Result

During testing, NeuroEye successfully tracked blink activity, gaze direction, and facial landmarks in real time using only a standard webcam. All data processing occurred within the browser via the MediaPipe Face Mesh pipeline — no server communication was needed at any point. Session outputs such as blink rate, gaze zone distribution, and mental state classification were displayed continuously on a live dashboard. Test data was collected across multiple sessions from different users. The dashboard presented results as time-series charts, classification scores, and gaze heatmaps, giving users an immediate view of their eye activity patterns. Across all test sessions, the system consistently identified differences in blinking and gaze behaviour between users who appeared relaxed and those who showed signs of stress or fatigue, which is in line with what the literature on ocular biomarkers predicts.

B. Discussion

The results from testing support the core hypothesis that eye-based signals can serve as meaningful proxies for mental state. Users who reported feeling stressed or anxious during testing showed more irregular blink patterns and less stable

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gaze behaviour compared to those who reported feeling calm — a finding that is consistent with the existing literature on ocular biomarkers. Accuracy also improved when blink statistics were evaluated together with gaze zone data, suggesting that a multi-signal approach gives a more reliable picture of cognitive and emotional state than any single metric alone. From a usability and design perspective, NeuroEye's commitment to webcam- only operation and local data processing proved to be a genuine advantage, making the system accessible to students, working professionals, and people in areas where clinical mental health resources are scarce. Since every session is entirely user-controlled and no data is stored externally, the system also meets the ethical requirements expected of digital health tools.

VII. CONCLUSION

NeuroEye shows that eye tracking powered by AI can be a practical and non-invasive way to support early mental health screening. The project validates those ocular signals — particularly blink rate and gaze behaviour — carry enough information to distinguish different mental states and flag early indicators of stress, fatigue, and mood- related conditions. The system achieves this while remaining accessible, private, and free of any installation requirements. Taken together, the results confirm that well-designed technology built around passive observation can meaningfully contribute to mental health awareness, particularly for populations that face real barriers to accessing professional care.

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