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NeuroEye: AI-Powered Eye Tracking for Mental Health Detection

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Abstract
Mental health remains one of the most underaddressed areas in global healthcare. Conditions such as depression, anxiety, ADHD, and chronic stress affect a significant portion of the population, yet countless individuals go through life without any form of screening or diagnosis. A major reason for this is that existing detection methods depend almost entirely on self-reported data — an approach that frequently breaks down when stigma, denial, or limited self- awareness gets in the way.To bridge this gap, we developed NeuroEye, a web-based application that identifies early indicators of mental distress by passively tracking how a person's eyes move and blink during a session. Rather than relying on questionnaires or interviews, the system uses a standard webcam to silently observe natural eye behaviour. It applies to the MediaPipe Face Mesh library to extract facial landmarks in real time and computes the Eye Aspect Ratio (EAR) to monitor blinking activity. Gaze direction is determined through iris position tracking across nine predefined zones. These combined signals are evaluated against established clinical thresholds to flag potential signs of stress, low mood, fatigue, or attention irregularities.A key design decision was keeping all computation on the user's own device — no data is transmitted to any external server, making the system entirely private. NeuroEye is not intended to replace professional medical evaluation.

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

1. Introduction
Mental health has long been treated as a secondary concern in public health systems worldwide, even as the number of people affected continues to rise. Conditions like depression, anxiety disorders, and attention-deficit related issues often develop slowly and quietly, which makes them hard to catch early — especially without a clinical evaluation. [1-5] The World Health Organization estimates that over 280 million people globally suffer from depression, and yet a surprisingly large proportion of them never receive any form of treatment. The reasons for this vary — some people can't afford care, others live in areas where mental health services simply aren't available, and many more avoid seeking help because of the social stigma that still surrounds mental illness. What makes this problem particularly tricky is that the tools we currently use for screening largely depend on self-reporting. Questionnaires and structured interviews can be useful, but they have real limitations. People may not always have self-awareness to recognize their own symptoms, or they may consciously downplay how they feel to avoid judgment. This makes it difficult to catch issues early, when intervention would be most effective. Interestingly, research over the past few decades has shown that the eyes can tell us quite a lot about a person's mental state. The way someone blinks, where they look, and how their gaze moves have all

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been linked to various neurological and psychological conditions. These are responses a person cannot easily control which makes them useful as reliable and objective indicators. NeuroEye was built around this idea. It's a lightweight browser-based application that uses a regular webcam to track eye behavior in real time. The system processes everything locally using MediaPipe's Face Mesh model, derives blink and gaze metrics from the video stream, and generates a session summary that the user can read privately or choose to share with a healthcare provider. There's no app to install, no account to create, and no data that leaves the device. The motivation behind the project goes beyond just building a technically functional tool. The goal was to create something that feels approachable — something a student, a remote worker, or someone in a rural area with limited access to mental health infrastructure could actually use without any friction. The following sections walk through the relevant research behind ocular biomarkers, explain how the system works, share observations from the current implementation, and discuss what future development could look like. Another significant aspect worth considering is how mental health tools are perceived by the people they are meant to help. Even when professional services are available, many individuals — particularly young adults and students — hesitate to engage with them. There is often a fear of being labelled, judged, or misunderstood. This psychological barrier is just as real as any physical or financial one, and it means that a significant portion of people who could benefit from early support never take that first step. A tool that works passively, without requiring any direct acknowledgment of a problem, has the potential to reach people who would otherwise remain completely outside the mental health system. It is also worth noting that NeuroEye does not attempt to monitor users continuously or collect data over long periods without consent. Each session is self-contained, user-initiated, and entirely under the individual's control. This design philosophy aligns with growing concerns around digital privacy and ethical data use in health technology. Rather than building a surveillance-style monitoring system, NeuroEye was intentionally designed to empower users — giving them clear information about their own physiological state and leaving all decisions about what to do with that information entirely in their hands, encouraging informed personal choices.

2. Literature Review

The idea that eye behavior can reflect a person's psychological state has been explored across neurology, psychiatry, and human- computer interaction for several decades, and their findings form the foundation that NeuroEye is built on Blink Rate as a Neurological Indicator: Karson (1983) was among the first to observe that spontaneous blink rate is closely tied to dopamine activity in the brain. His work showed that conditions like Parkinson's disease and schizophrenia, which affect dopamine regulation, also produce noticeable changes in blinking frequency. Zaman and Choudhury (2021) later extended this to mental health, finding that individuals with depression or anxiety often blink outside the normal adult range of 12 to 22 times per minute. Thibaut et al. (2020) studied children with ADHD and found that the irregularity in blink timing was just as significant as the blink count itself, suggesting that both frequency and consistency matter. Eye Aspect Ratio for Blink Detection: Soukupova and Cech (2016) designed a geometric method for detecting blinks using six landmark points placed around each eye. Their Eye Aspect Ratio (EAR) measures how open the eye is at any given moment, dropping sharply during a blink and recovering immediately after. Their experiments showed that an EAR value below 0.21 worked consistently for detecting blinks, and this number has been widely used in later eye-tracking work, including ours. Drutarovsky and Fogelton (2014) confirmed that this approach holds up well in real-world conditions, particularly when smoothing is applied to reduce frame-level noise. Facial Landmark Detection: The Face Mesh pipeline from Lugaresi et al. (2019) made it possible to track 468 facial points in real time without needing any special hardware — just a standard webcam — which made it a practical choice for browser-based systems like NeuroEye. Kartynnik et al. (2019) reported localization errors

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below 2mm under normal conditions, which is sufficient for both EAR calculation and iris-based gaze tracking. A later update added iris-specific landmarks, making it possible to estimate gaze direction entirely within a browser environment — something that was previously only achievable with dedicated hardware. Browser-Based Machine Learning: Smilkov et al. (2019) showed that running ML models inside a browser was not just possible but fast enough to be useful — something that directly influenced NeuroEye's decision to use a client-side processing approach. For NeuroEye this was a key finding — it meant the entire system could operate on the user's device without transmitting any biometric data externally, which directly addresses privacy concerns around digital health tools. Research Gap While each of these techniques has been well studied individually, combining them into a unified mental health screening tool remains relatively unexplored. Most existing work focuses on driver drowsiness or clinical setups with specialized equipment. NeuroEye aims to bridge that gap by integrating these components into a single accessible, privacy-preserving, browser- [6-10]

3. Methodology

NeuroEye works through a structured four-stage pipeline that takes raw webcam input and converts it into meaningful mental health signals, all within the browser without any server involvement. System Architecture The application is built as a single-page web interface using HTML5, CSS3, and JavaScript. Core libraries including MediaPipe Face Mesh and Chart.js are loaded with CDN sources, keeping the setup simple and installation-free. The processing flow works-based framework as follows — the webcam stream is captured and continuously sent to the Face Mesh model, which returns facial landmark coordinates for each frame. From these coordinates, the system calculates blink and gaze metrics. These metrics are then evaluated by a threshold-based inference engine, and the results appear on a live dashboard. At the end of the session, everything gets compiled into a downloadable report. Data Collection and Signal Processing During a session, the system records three types of data. Ocular data covers EAR values, iris coordinates, blink timestamps, and blink duration. [11-15]

Gaze data records normalized iris displacement across nine directional zones — center, the four cardinal directions, and the four diagonals. Statistical measures include blink frequency in blinks per minute, the Coefficient of Variation (CV) of inter-blink intervals, and average blink duration. 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 prevent single noisy frames from triggering false readings, the raw EAR values are smoothed using a rolling average over three frames. A blink is only counted when the smoothed EAR stays below 0.21 for at least two frames in a row. Gaze zone is determined by calculating how far the iris has shifted from the center of the eye region and assigning it to the closest of the nine predefined zones. Inference Engine and Alert Mechanism The inference engine takes the processed metrics and maps them to possible mental health signals based on the following rules:

- 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

Once the session ends, a plain-text report is generated that summarizes all the measured values, the primary signal classification, gaze zone distribution across the session, and general recommendations based on the findings. [16-20]

The user can save this report locally or share it directly with a healthcare professional for further evaluation. Figure 1.

4. Block Diagram

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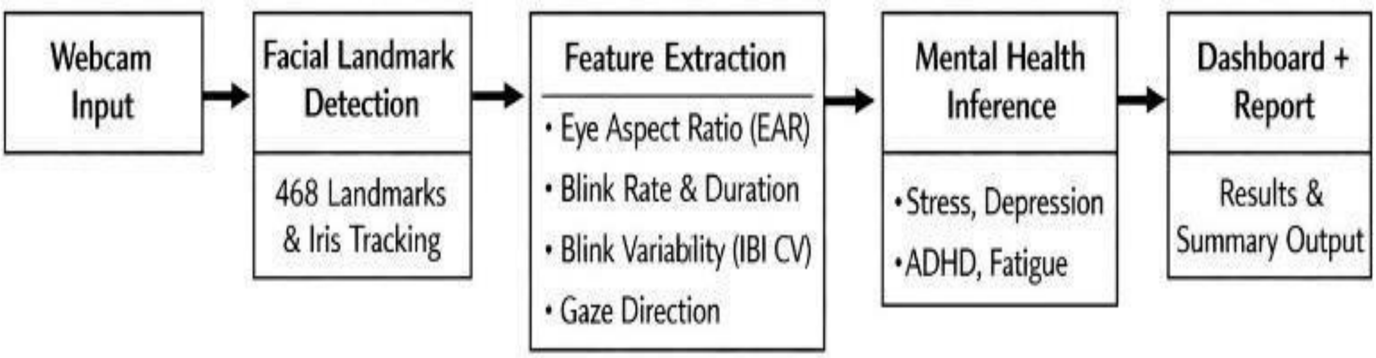

Figure 1 Block Diagram

5. Flowchart

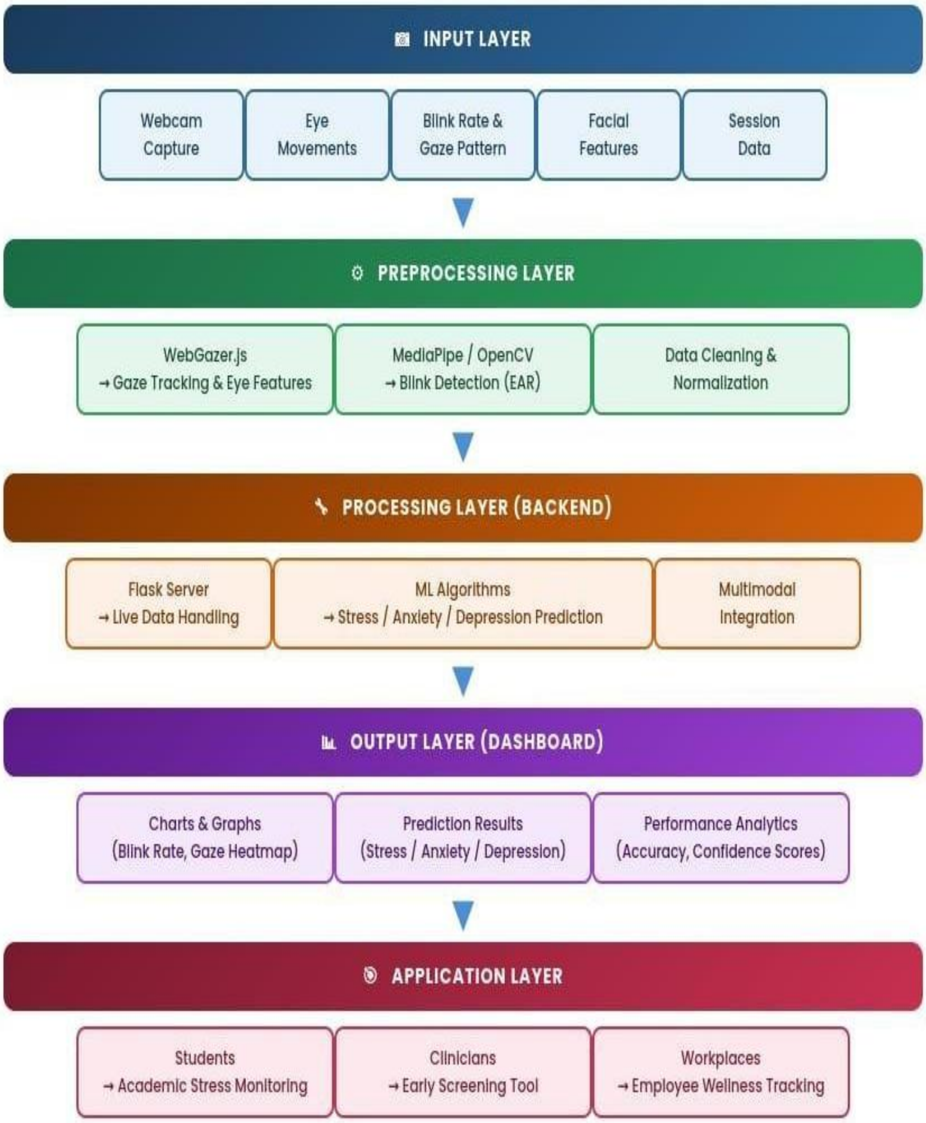

Figure 2 Neuro Eye System Architecture and Data Flow

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6. Result & Discussion

6.1.Results

NeuroEye was designed to track eye movements, blink frequency, and facial landmarks using a standard webcam. Data was processed entirely within the browser using the MediaPipe Face Mesh pipeline, which extracted real-time blink and gaze metrics without any server-side computation. Session outputs including blink rate, gaze zone distribution, and stress classification were displayed on a live dashboard.Data recorded during testing included blink rate and gaze positioning over multiple trials. Users could see results in various forms — such as charts, prediction scores and heatmaps – in the dashboard that users can visualize their mental health indicators real time. Throughout testing, the system reliably picked up differences in blinking patterns and gaze behaviour between users who appeared calm and those showing signs of stress or fatigue — results that are consistent with what existing research tells us about these ocular signals. Figure 2 shows Neuro Eye System Architecture and Data Flow

6.2.Discussion

Observations from the testing phase support the hypothesis that ocular biomarkers can serve as meaningful indicators of mental health. Participants who self-reported stress or anxiety more frequently exhibited irregular blink patterns and unstable gaze behavior, which aligns with findings in existing literature. Performance improved further when blink metrics were analyzed alongside gaze distribution data, suggesting that combining multiple ocular signals yields a more complete picture of cognitive-emotional state. From a design standpoint, the system's emphasis on accessibility and privacy proved to be a meaningful differentiator. NeuroEye requires only a webcam, making it usable by students, employees, and individuals in underserved areas — a practical advantage over specialized clinical instruments each session is user-initiated and self-contained, ensuring that data remains under the individual's control. This approach not only reduces barriers to mental health screening but also aligns with ethical standards for digital health technologies

Conclusion

NeuroEye demonstrates that AI-powered eye tracking can be an effective, non-invasive method for early mental health detection. The project confirms that ocular biomarkers such as blink rate and gaze fixation can provide meaningful insights into stress and emotional states. By combining technical robustness with user-friendly design, NeuroEye empowers individuals to monitor their well-being while maintaining privacy and control. This work validates the problem identified in the results and discussion section and shows that accessible technology can play a vital role in proactive mental health care. [21-24]

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