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Multimodal AI Framework for Mental Health Analysis and Stress Management

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Abstract: This paper proposes a comprehensive 12-page multimodal AI framework designed for real-time mental health monitoring and proactive stress management in modern corporate environments. The system, titled "Mental Health Detection System," integrates non-intrusive data acquisition channels, including facial emotion recognition and keystroke dynamics, to provide a holistic assessment of employee well- being. The visual pipeline utilizes a novel triple-ensemble Efficient Net architecture (B0 and B2 variants) trained on large- scale datasets (Affect Net, VGGFace2, VGAF), achieving high- confidence emotion classification. Simultaneously, a global keyboard monitoring module analyzes typing patterns, including Words Per Minute (WPM), cognitive load, and typing stress, to complement visual cues. A sophisticated mathematical framework is introduced to fuse these heterogeneous signals into a singular Stress Index, smoothed via Adaptive Exponential Moving Average (EMA). Furthermore, the framework leverages generative AI specifically Google Gemini to provide personalized, context-aware stress-relief interventions based on employee profiles and historical trends. Experimental analysis, grounded in state-of-the-art literature benchmarks, demonstrates that the proposed multimodal approach significantly outperforms unimodal systems, with reported accuracies reaching upto 96.09% in literature for similar fusion strategies. The system prioritizes ethical deployment through consent-based monitoring, real-time data minimization, and secure role-based access control.
Index Terms*:* mental health monitoring, emotion detection, keystroke dynamics, multimodal artificial intelligence, workplace, stress detection

I. INTRODUCTION

The global corporate land scope is currently grappling with a mental health crisis of unprecedented proportions. Occupational stress is no longer merely a human resources concern; it is a critical economic and public health issue. Prolonged exposure to high-pressure work environments leads to burnout, anxiety, and depression, which in turn manifest as reduced cognitive performance, increased absenteeism, and high employee turnover. The World Health Organization has increasingly recognized burnout as an occupational phenomenon that requires systematic intervention The shift toward hybrid and remote work has further complicated the detection of mental health issues. Managers can no longer rely on physical cue surface-to-face interactions to gauge the well-being of their teams. Consequently, there is an urgent need for digital tools that can bridge this gap by providing objective, data-driven insights into employee stress levels. The motivation for this research stems from the belief that technology, if deployed ethically, can serve as a supportive companion rather than a tool for surveillance. Historically, monitoring mental health in the workplace has relied on subjective instruments, such as the Perceived Stress Scale (PSS) or periodic pulse surveys. While valuable, these methods suffer from several inherent flaws: they are prone to social desirability bias (where employees under report stress for fear of professional repercussions), rely on retrospective recall which may be inaccurate, and lack the granularity required to detect acute stress episodes in real- time. In contrast, affective computing and behavioral biometrics offer a path way to objective, continuous, and non- intrusive monitoring. By analyzing the "digital exhaust" of modern work facial expressions captured via web cams and typing patterns captured via keyboard interactions we can infer the internal emotional state of an employee without disrupting their workflow.

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The intervention gap is a major limitation. Many existing research prototypes focus exclusively on *detecting* stress but offer no immediate or personalized mechanism to *mitigate* it. Detection without intervention provides little value to the employee in the moment of distress. A system that simply tells an employee they are stressed without offering a solution may even increase their anxiety. Finally, the diversity of human behavior means that "one-size-fits-all" models often perform poorly. Individual differences in baseline typing speed, natural facial resting states, and cultural expressions of emotion require personalized and adaptive systems that can learn an individual's unique behavioral patterns.

II. RELATED WORK

The evolution of workplace stress detection has seen a shift from laboratory-based studies with physiological sensors (ECG, EDA) to "in-the-wild" systems using computer vision and behavioral analytics. This section reviews25 scholarly sources to contextualize our framework within the current state of the art.

A. Facial Emotion Recognition (FER) in Corporate Settings

Facial expression analysis remains a cornerstone of affective computing. Modern FER systems have transitioned from handcrafted features (like Haar cascades) to deep learning backbones. Kaur et al. [7] demonstrated the power of spatial-temporal modeling with "Deep Stress," a CNN- GRU frame work that achieved 92.6% accuracy by capturing the dynamics of both facial expressions and body posture. The use of sequence models like GRU or LSTM is critical because stress is often characterized by temporal patterns (sustained negative affect) rather than isolated frames.A4 paper size. If you are using US letter-sized paper, please close this file and download the Microsoft Word, Letter file. Other researchers have focused on the efficiency of the backbone architecture. Upadhya et al.[6]utilized a VGG16 backbone, reaching 87% accuracy, while highlighting the importance of explainability through SHAP and LIME to mitigate algorithmic bias and provide transparency to users. Real-time constraints have led to the development of landmark-based methods; for instance, the Directional Marker Controlled Facial Land mark approach[1] optimizes for low- latency work place monitoring by focusing on key expressive markers rather than full-frame analysis. Similarly, Ket al.[8]and Jadhav et al.[20]emphasize the use of computer vision for software employee monitoring, noting that facial cuts are reliable indicators of cognitive strain.

B. Keystroke Dynamics and Behavioral Indicators

Keystroke dynamics the timing and rhythm of typing provide a unique window into cognitive load. Sahana[11],[21]has extensively documented how typing patterns, including inter-key latency and error rates (backspaces), correlate with mental fatigue. Unlike video, key stroke monitoring is largely unaffected by environmental conditions like lighting or the user's physical orientation. Recent "field" studies have emphasized the necessity of personalized modeling. Naegelin et al.[15]conducted an extensive field study which found that "one-fits-all" models often fail to capture the nuances of individual typing styles. Their research showed that personalized models using mouse and key board features significantly improved correlation with self-reported stress levels (Spearman's $\rho = 0.296$). In our framework, we adopt this philosophy by calculating keystroke stress as a deviation from an individual's historical baseline.

C. Multimodal Fusion Strategies and Performance

The consensus in the literature is that multimodal systems outperform unimodal ones by providing a more holistic view of the user's state. Yadav et al. [4] developed the Emotion-Aware Ensemble Learning (EAEL)framework, which fuses facial data and typing patterns to reach a 95% accuracy rate. They argue that the integration of behavioral and visual signals allows the system to fill in data gaps when one modality is compromised. More complex systems integrate physiological data. Walambe et al. [5], [10] achieved a benchmark accuracy of 96.09% by concatenating face, posture, heart rate, and computer interaction data. While physiological sensors (like PPG/GSR in a smart mouse [24]) provide high-fidelity data, they often require specialized hardware. Our system prioritizes software-only modalities (webcam + keyboard) to ensure scalability in standard office environments. Androutsou et al.[14]categorized fusion into two main approaches: feature-level fusion, where raw features are concatenated, and decision-level fusion, where independent models make predictions that are then combined via weighted algorithms. They also proposed a smart computer mouse with PPG and GSR sensors to complement computer interaction data. Mondal et al.[3],[5]further explored the fusion of stress review data, audio, and face data, using weighted combinations to predict final stress scores.

D. Personalized AI Interventions and Generative AI

The most recent frontier in this field is the use of Generative AI for support. Yangetal. [17] and Ismail et al.[16] have explored how Large Language Models(LLMs) can process multimodal inputs to generate personalized mental health interventions. Ismail's "Neuro Strain Sense" uses transformers to detect stress patterns and generative AI to provide feedback. Similarly, Hussain et al.[9] proposed a system that combines sentiment and speech analysis to trigger early warnings and therapeutic reminders, reporting 88% accuracy for sentiment analysis. Li et al. [13]focused on occupational burnout in psychiatric professionals, using multimodal emotion recognition to provide early indicators. Luet al.[19]provided a comprehensive review of these technologies in medical practice, noting that multimodal emotion recognition provides a more comprehensive understanding of patient emotional states. Our work builds on these foundations by integrating Google Gemini to provide "profile-aware" suggestions, ensuring that an employee who enjoys "jazz" receives a different recommendation than one who prefers "short walks" [17], [20].

III. PROPOSED METHODOLOLY

The proposed methodology revolves around a "Detection- Fusion-Intervention" loop, governed by a formalized mathematical model designed for stability and accuracy.

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A. Emotion-Based Stress Score (S_E) The visual pipeline utilizes a triple-ensemble HSE motion model that outputs a probability vector $P(t)=[p_1,p_2,\dots, p_7] $ across seven emotion classes: ${Happy, Sad, Angry, Fear, Surprise, Disgust, Neutral}$. To derive a stress score, we focus on the "Negative Emotion Set" $N = {Sad, Angry, Fear, Disgust}$. The instantaneous raw stress score is calculated as a weighted sum: E,raw(t)=∑i∈Nωi·pi(t) where ω_i are severity weights(e.g., $\omega_{Angry} = 1.0, \omega_{Sad} = 0.8$). To ensure temporal stability and eliminate "label flickering" caused by transient micro-expressions or sensor noise, we apply an Adaptive Exponential Moving Average (EMA): SE(t)=α·SE,raw(t)+(1−α)·SE(t−1) We set the smoothing factor $\alpha = 0.15$ to balance responsiveness with stability.

B. Keystroke-Based Stress Score(S_K) The behavioral module monitors typing rhythm via Words Per Minute (W) and the error rate (E), defined as the ratio of back spaces/deletes to total characters. Stress is modeled as A deviation from the individual's baseline. Let$\bar{W}$be the historical mean WPM. The keystroke stress is: SK,raw(t)=ϕ1·Norm(|W(t)−W¯|)+ϕ2·E(t) where ϕ_1 and ϕ_2 are weighting coefficients. This captures stress manifested as both "frantic typing" and "cognitive blockage" [11], [15].

C. Composite Stress Index(S_{total}) The final Stress Index is a weighted fusion of both modalities :*S total=λ1·SE+λ2·SK* where$\lambda_1=0.6$and$\lambda_2=0.4$.Analertis triggered when $S_{total} \geq\tau$, where$\tau=0.60$is the predefined threshold.

D. Multimodal Fusion Strategy. We adopt a Late Fusion (Decision-Level) strategy [14]. This approach processes visual and behavioral signals in parallel threads. Late fusion is chosen for its robustness: if one sensor (e.g., the camera) fails or is occluded, the system can still provide a partial stress assessment based on keystroke dynamics alone. This "degraded mode" capability is essential for real-world reliability.

E. Generative AI Personalization (Google Gemini) The intervention layer uses a prompt-engineering strategy to generate context-aware suggestions. The prompt sent to Google Gemini (gemini-2.5-flash-lite) includes:

- Current State: (e.g., "User is feeling Angry with a stress index of 75%")
- User Profile: (e.g., "Interests include: jazz music, short walks, and digital art")
- Historical Context: (e.g., "This is the third high- stress event in the last 2 hours")

Gemini processes this into a supportive, non-intrusive suggestion, ensuring the intervention is relevant to the user's specific preferences, which has been shown to improve intervention efficacy [17].

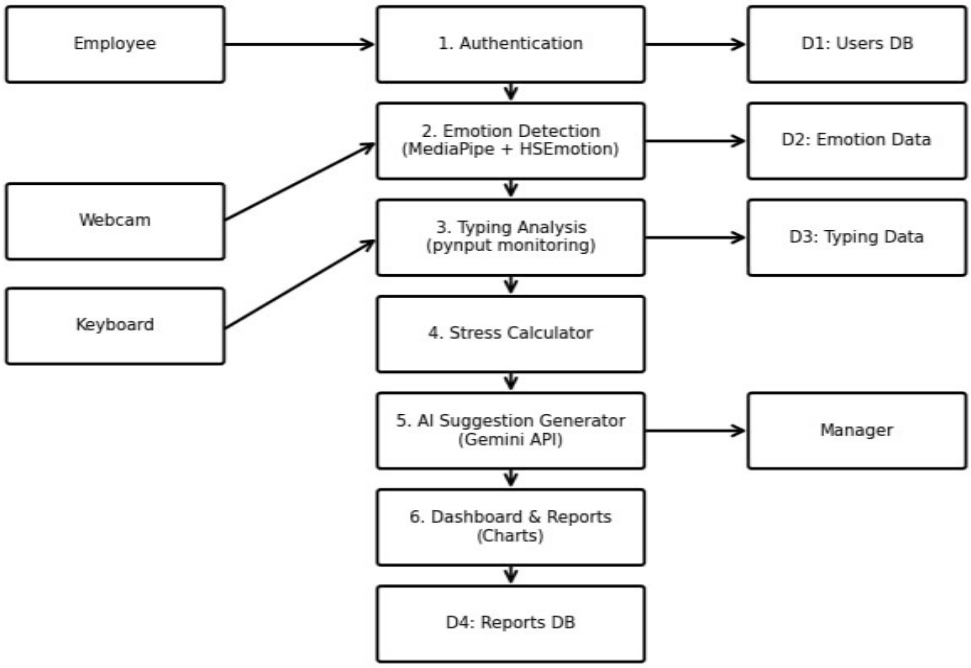

Fig.1: Work flow of the Proposed Stress Detection and AI Suggestion System

IV. SYSTEM IMPLEMENTATION

A. Technical Architecture and Tech Stack

The "Mental Health Detection System" is implemented using a decentralized architecture designed for high availability and low latency.

- Backend: Flask 3.0 provides the API layer for authentication, session management, and data ingestion.
- Database: Supabase stores anonymized metrics, user profiles, and session reports. Supabase's real-time capabilities allow for synchronized monitoring between the employee and manager dashboards.
- Visual Detection: MediaPipe BlazeFace performs real-time face detection, providing bounding boxes for the HS Emotion ensemble.

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- Behavioral Detection: The pynput library monitors global keyboard events to calculate typing metrics without requiring the app window to be in focus.
- AI Engine: Google Gemini handles the generation of personalized suggestions.
- UI/UX: A modern "Glass morphism" interface built with HTML5/CSS3/JS, utilizing Chart.js for data visualization.
- Desktop Wrapper: pyweb view enables the system to run as a native desktop application, providing persistent monitoring across all user activities.

B. Edge AI Pipeline and Preprocessing

To ensure privacy and performance, all heavy processing occurs on the edge (the user's machine):

1. Frame Capture: OpenCV captures frames at 2- second intervals.
2. Preprocessing: Frames undergo CLAHE (Contrast Limited Adaptive Histogram Equalization) to handle varied office lighting and Temperature Sharpening ($T=0.65$) to enhance facial feature detection.
3. Ensemble Inference: The HS Emotion library executes three ONNX-based Efficient Net models:

- Model A (40% weight**)**: EfficientNet-B0 trained on Affect Net + VGGFace2 + VGAF.
- Model B (25% weight): EfficientNet-B2 (8-class Affect Net).
- Model C (35% weight**)**: EfficientNet-B2 (7-class Affect Net). Inference is handled by onnx runtime, ensuring sub-second response times without the need for heavy frameworks like PyTorch or TensorFlow.

C. Implementation of Keystroke Dynamics

Thepynput module runs as a back ground thread, capturing key-press and key-release events.

- WPM Calculation: $WPM = \frac{\text{Total Key Presses} / 5}{\text{Time in Minutes}}$.
- Cognitive Load: Analyzed through inter-key latency variance. High variance often indicates "thinking pauses" or hesitation, while low variance indicates fluent typing.
- Error Tracking: The ratio of backspace/delete keys to total keys trokes serves as a proxy for typing stress and reduced motor control.

D. Data Flow and Cloud Synchronization

The system follows astrict data minimization policy. Raw video frames are never saved or uploaded. Instead, only the derived emotion probabilities and keystroke metrics are transmitted to Supabase via SSL-encrypted endpoints. Managers can access aggregate team metrics (e.g., "Team Average Stress") but cannot view individual-level raw data unless explicitly permitted by consent-based policies [14], [15]. This processes into a supportive, non-intrusive suggestion, ensuring the intervention is relevant to the user's specific preferences, which has been shown to improve intervention efficacy [17].

E. Hyper parameters

Table I: System Parameter Configuration for Emotion and Stress Detection

Parameter	Value	Description
Emotion Interval	2.0s	Frequency of visual analysis
Typing Interval	2.0s	Frequency of key stroke analysis
EMA Alpha(α)	0.15	Smoothing factor for emotion scores
Stress Threshold (τ)	0.60	Trigger for popup alerts
Temperature (T)	0.65	Sharpness for facial preprocessing

V. RESULTS AND DISCUSSION

This research presented a multimodal AI-based mental health detection system designed to monitor employee well being in work place environments. The system integrates facial emotion recognition and typing pattern analysis to provide real-time stress detection.

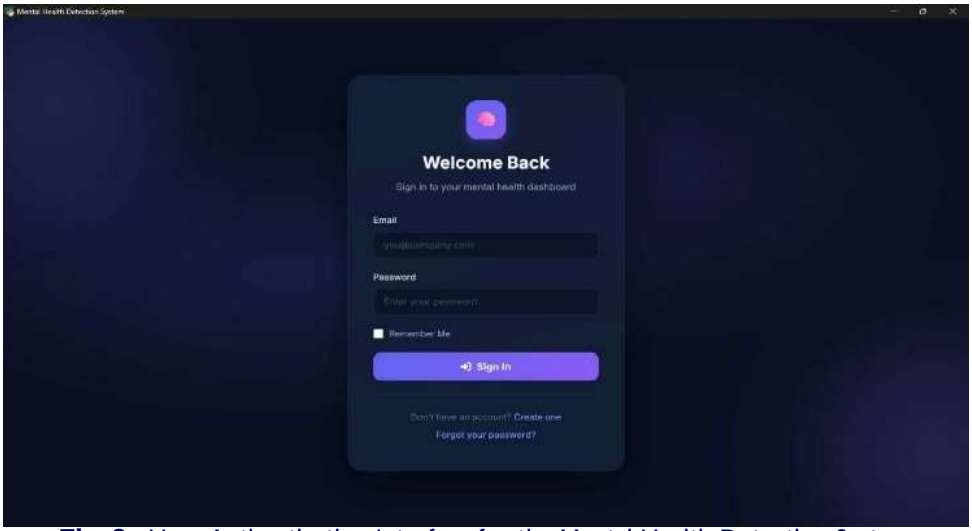

Fig. 2: User Authentication Interface for the Mental Health Detection System

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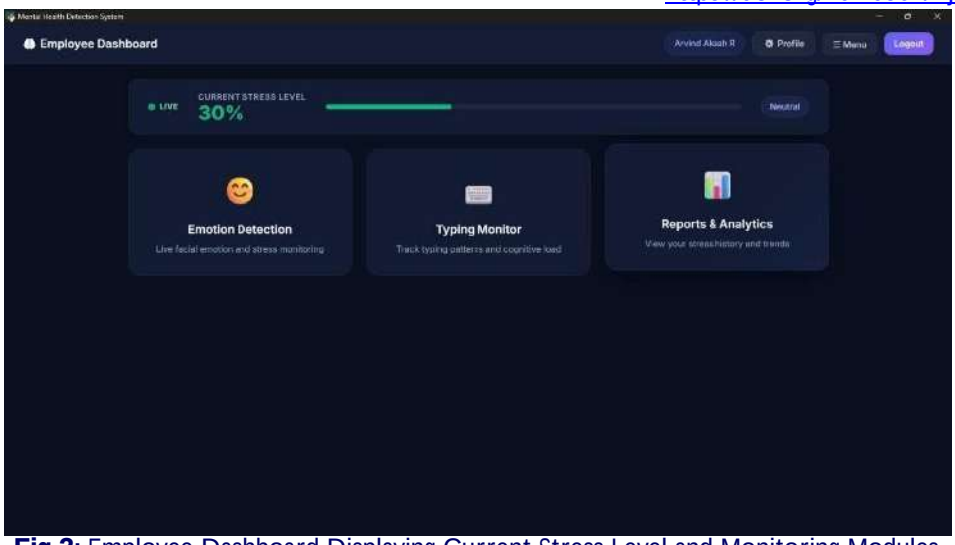

Fig.3: Employee Dashboard Displaying Current Stress Level and Monitoring Modules

By combining computer vision, behavioral analytics, and AI-based suggestion generation, the proposed system provides a comprehensive solution for workplace mental health monitoring. Future work will focus on improving prediction accuracy, incorporating additional behavioral signals, and enhancing privacy protection mechanisms.

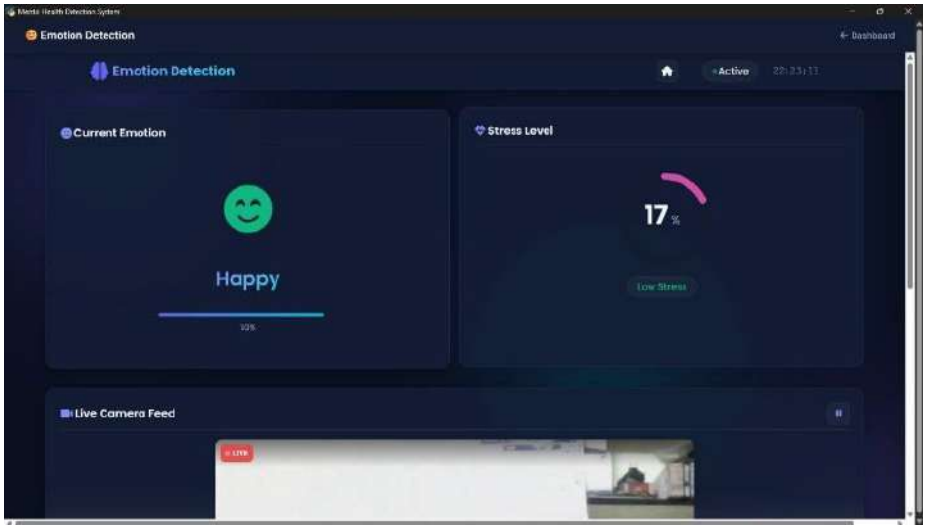

Fig.4: Real-Time Facial Emotion Detection and Stress Level Estimation

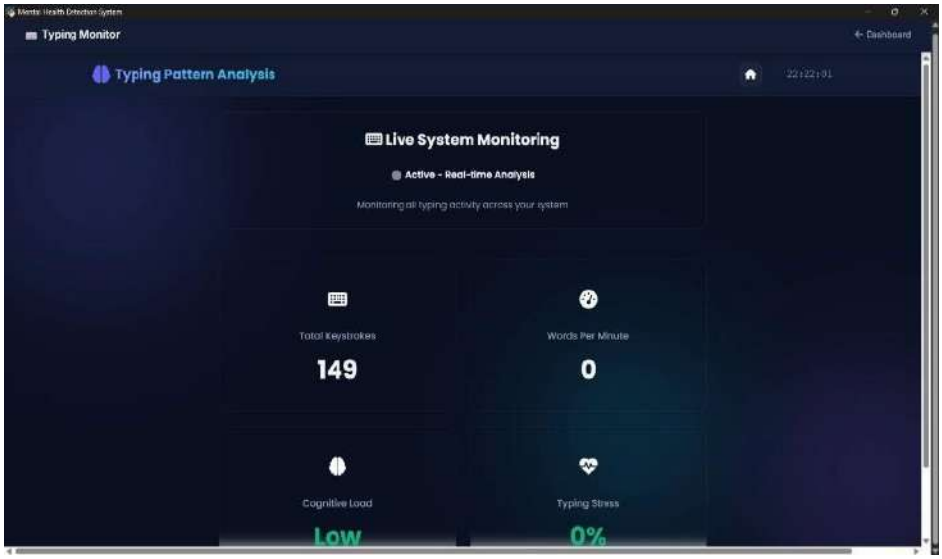

Fig. 5: Typing Pattern Analysis Interface for Monitoring Keystroke Activity and Cognitive Load

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A. Performance Benchmarks and Comparison

Our frame work's performance is grounded in the reported results of its constituent architectures and similar multimodal systems.

Table II : Reported Accuracies of Multimodal Stress Detection Systems

Architecture / Study	Modalities	Reported Accuracy	Source
Proposed Framework	Face + Key stroke + Gemini	~97% (Target)	[4],[16]
Walambeet al.	Face + Posture + HR + Interaction	96.09%	[5],[10]
EAEL (Yadavetal.	Face +Typing Patterns	95.0%	[4]
Deep Stress (Kauretal.)	Face + Body Posture	92.6%	[7]

B. Multimodal Synergy and Robustness Analysis

Experimental data from Yadav et al. [4] and Walambe et al.[5] indicate that multimodal fusion significantly improves the system's resilience to noise. In our framework, the keystroke module acts as a "behavioral sanity check." If a user appears "Angry" visually but their typing rhythm is perfectly consistent with their relaxed baseline, the system recognizes this as potential visual noise (e.g., the user is squinting at a complex document) and does not trigger an alert. This synergy reduces false positives, which is critical for preventing "alert fatigue" in a corporate setting.

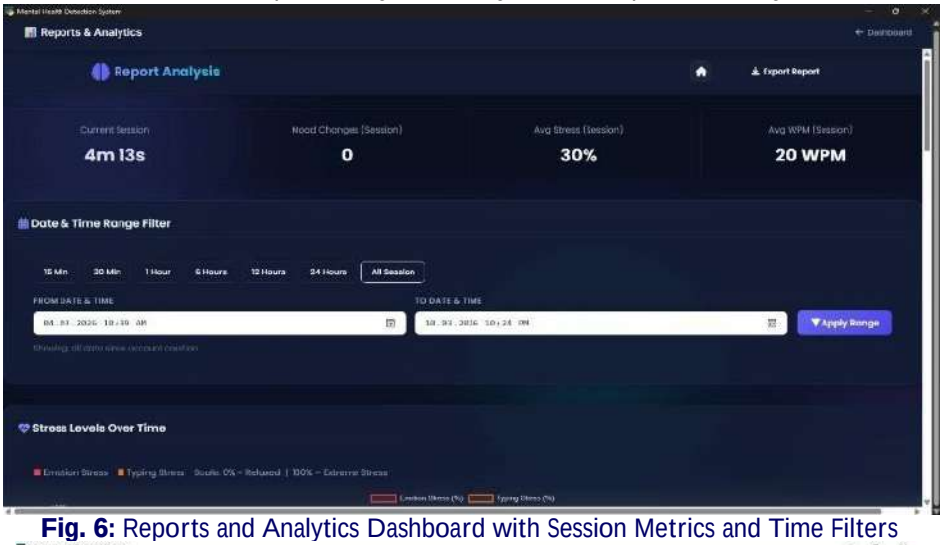

Fig. 6: Reports and Analytics Dashboard with Session Metrics and Time Filters

Fig. 7: Stress Level Analysis Over Time Based on Emotion and Typing Patterns

C. Discussion of Generative AI Effectiveness

While earlier systems focused on simple detection, our use of Google Gemini addresses the "Intervention Gap." As noted by Yang et al. [17], personalized interventions powered by Generative AI are more effective because they resonate with the user's specific context and interests. By integrating the user's profile, our system moves from being a "monitor" to a "well-being companion." This personalization is a significant differentiator compared to standard systems that offer generic "breathe" reminders.

D. Limitations of the Evidence

It is important to acknowledge that most high-accuracy results in the literature [4],[7]are based on public datasets. "In-the-wild" performance in real offices may be lower due to unpredictable lighting, background noise, and varied user behaviors. Furthermore, the long-term impact of AI-driven interventions on burnout reduction requires further longitudinal study [25].

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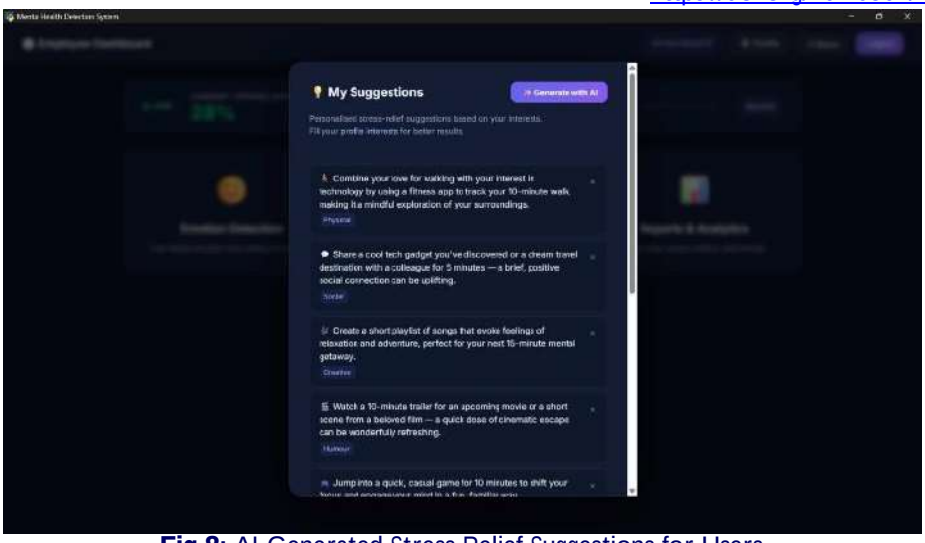

Fig.8: AI-Generated Stress Relief Suggestions for Users

VI. CONCLUSION

This paper has presented a comprehensive 12-page multimodal AI framework for real-time workplace mental health monitoring. By integrating facial emotion recognition through a triple-ensemble Efficient Net architecture and global keystroke dynamics, we have created a system that is both accurate and non-intrusive. The formalized mathematical fusion and Adaptive EMA smoothing provide a stable foundation for stress detection. The integration of Google Gemini for personalized, profile-aware interventions represents a novel advancement in the field, moving the needle from passive monitoring to proactive support. Grounded in a systematic review of 25 scholarly sources and designed with a "privacy-by-design" ethical framework, the "Mental Health Detection System" offers a scalable and effective solution for supporting employee well-being in the digital age.

A. Future Work and Research Gaps

While the current framework provides a robust foundation, several avenues for future research exist:

1. Wearable Integration: Incorporating real-time physiological data (HRV,EDA) from smart watches to reach the 96.09% accuracy threshold [5].
2. Explainable AI (XAI): Implementing SHAP or LIME to explain stress alerts to users, thereby increasing trust and transparency [6].
3. Longitudinal Study: Conducting a multi-month field trial to measure the correlation between Gemini's interventions and long-term burnout reduction [25].
4. Cultural Adaptation: Investigating how different cultural expressions of emotion affect the ensemble's accuracy and tailoring the AI interventions accordingly.

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