Silent Emotional Burnout Detection System Using Behavioral Artificial Intelligence

Komal Pandey[1], Adnan Ansari[2], Shoheb Mulla[3], Divyesh Shinde[4]
[1,2,3,4]*Department of Computer Science, Bharat College of Engineering, Badlapur, Thane, Maharashtra, India*

Prof. Sonali Patil
Department of Computer Science and Engineering (AIML), Bharat College of Engineering,Badlapur, Thane, Maharasht

***Abstract*—Emotional burnout is a silent psychological epidemic that undermines productivity, mental health, and decision-making in digital-heavy environments. Existing detection methods rely on intrusive modalities such as facial expression analysis, speech processing, or self-reported questionnaires, raising privacy and scalability concerns. This paper proposes a Silent Emotional Burnout Detection System leveraging Behavioral Artificial Intelligence (AI) to infer burnout risk from non-intrusive user interaction patterns: typing speed, keystroke intervals, idle time, error rate, and task-switching frequency. The system employs a hybrid machine learning pipeline combining unsupervised techniques (K-Means clustering, Isolation Forest anomaly detection) with supervised classifiers (Support Vector Machine, Random Forest). Evaluated on a dataset of 1,000 simulated users, our approach achieves 92% accuracy and 0.91 F1-score, with SVM outperforming other models consistent with recent findings [1]. The system is privacy-preserving, hardware-free, and suitable for continuous deployment in remote work and e-learning contexts.**

***Index Terms*—Burnout Detection, Behavioral AI, Keystroke Dynamics, Human-Computer Interaction, Anomaly Detection, Support Vector Machine**

I. INTRODUCTION

Burnout, defined by the World Health Organization as an "occupational phenomenon" resulting from chronic workplace stress, is characterized by emotional exhaustion, depersonalization, and reduced personal accomplishment [2]. The global shift to remote work and digital learning has obscured traditional physical cues, making early detection increasingly challenging [3].

Behavioral AI offers a scalable alternative by analyzing subtle human-computer interaction (HCI) signals as proxies for cognitive fatigue. Unlike vision-based systems requiring cameras or wearables, behavioral modalities such as keystroke dynamics operate silently in the background, preserving user privacy [4]. Recent work demonstrates that SVM-based models can predict burnout risk with high fidelity using behavioral and work-related features [1], while longitudinal activity logs effectively capture evolving burnout patterns [5].

Contributions

1. A novel feature set derived from ambient HCI logs (typing rhythm, idle patterns, task switches).
2. A hybrid ML pipeline integrating unsupervised anomaly detection with supervised classification, achieving 92% accuracy.
3. A privacy-first deployment blueprint requiring no cameras, microphones, or wearables.

This work extends keystroke dynamics research [4], [6] and passive AI frameworks [3] by focusing exclusively on unlabeled behavioral data, making it suitable for real-world organizational deployment.

II. LITERATURE REVIEW

A. Machine Learning for Burnout Prediction

Supervised learning has shown strong performance in burnout risk stratification. Sharma et al. [1] evaluated KNN, Random Forest, and SVM on the Hacker Earth Employee Burnout Challenge dataset, with SVM achieving the highest predictive performance ($ R^2 = 0.84 $) via 30-fold cross-validation. Their interactive Streamlit interface demonstrates practical organizational applicability.

HiPAL (Hierarchical burnout Prediction based on Activity Logs) introduced by Saha et al. [5] represents the first end-to-end deep learning framework for physician burnout prediction using electronic health record (EHR) activity logs. By learning deep representations from 15 million clinician logs, HiPAL captures both short-term and long-term burnout evolution through a semi-supervised transfer learning approach.

B. Passive and Behavioral AI Approaches

Passive AI systems monitor stress and burnout through continuously collected behavioural and physiological biomarkers [3]. Hernández et al. [3] reviewed frontline worker studies, identifying email response latency, task-switching frequency, and after-hours activity as key digital phenotypes.

However, they note limitations in cross-sector generalizability and long-term validation.

Keystroke dynamics research establishes that typing rhythm, key hold duration, and inter-key latencies correlate with emotional states [4]. Epp et al. [4] demonstrated that features such as flight time variance and key press duration can identify stress and frustration with 80%+ accuracy. Recent work by Zhang et al. [6] confirms that multifractal properties of typing patterns significantly degrade under cognitive fatigue, enabling real-time fatigue detection.

C. Work Pattern Monitoring

AI-driven work pattern monitoring reveals that prolonged working hours, irregular activity cycles, and reduced engagement strongly predict burnout [7]. Kumar et al. [7] highlighted Microsoft's AI-powered well-being dashboard, which monitors meeting schedules, after-hours emails, and collaborative tool engagement to suggest personalized interventions.

D. Theoretical Foundations

The Pleasure-Arousal-Dominance (PAD) emotional framework [8] provides a dimensional model for mapping behavioral signals to affective states. The Maslach Burnout Inventory (MBI) remains the gold-standard psychometric tool, defining burnout's three core dimensions [9]. Our system operationalizes these theories through behavioral proxies: reduced typing speed (exhaustion), increased errors (reduced accomplishment), and erratic switching (cynicism).

Research Gap: No existing system combines fully non-intrusive HCI logging with hybrid unsupervised-supervised learning for unlabeled data scenarios.

III. EXISTING SYSTEMS AND LIMITATIONS

A. Current Approaches

Method	Modality	Accuracy	Limitations
Facial Expression Analysis	Camera-based	85–90% [10]	Intrusive, privacy concerns
Speech Sentiment Analysis	Microphone-based	80–88%	Background noise sensitivity
MBI Questionnaires	Self-report	Gold standard [9]	Subjective, infrequent
Wearable Sensors	Physiological (HRV)	75–85% [3]	Hardware dependency, discomfort
HiPAL [5]	EHR Activity Logs	88% (AUC)	Healthcare-specific, requires EHR access

B. Key Limitations

1. Intrusiveness: Camera/microphone requirements violate privacy norms [3].
2. Hardware Dependency: Wearables impose cost and adoption barriers [3].
3. Label Dependency: Supervised models require costly annotated datasets [5].
4. Domain Specificity: EHR-based systems do not generalize to students or knowledge workers [5].

Our system addresses these gaps through ambient keyboard/mouse logging, unsupervised pre- training, and domain-agnostic features.

IV. PROPOSED SYSTEM

A. System Overview

The Silent Emotional Burnout Detection System infers burnout risk $r \in [0,1]$ from behavioral signals captured via standard OS APIs (e.g., Windows ETW, Linux evdev, Python's pynput).

Design Principles:

- Non-intrusive: No cameras, microphones, or wearables.
- Privacy-preserving: Local processing; no keystroke content logged.
- Unsupervised-first: Operates on unlabeled data initially.
- Real-time: Sub-second inference latency.

B. Target Users

- Remote professionals (IT, finance, consulting).
- Online students (e-learning platforms).
- Frontline knowledge workers (customer support, content moderation).

V. METHODOLOGY

A. Data Collection Module

A lightweight Python agent logs the following events (content-agnostic):

1. Keystroke Events: Timestamp, key code (not character), hold duration.
2. Mouse Events: Clicks, scrolls, idle periods.
3. Application Focus: Window title hash (for task-switching).

Derived Metrics:

- Typing speed: $v = \frac{N_k}{T}$ (keystrokes/second).
- Idle duration: Consecutive seconds without input (>30s threshold).
- Error rate: Backspace/Delete events per 100 keystrokes.
- Task-switch frequency: Application focus changes per minute.

Dataset: Simulated 1,000 users (50% burnout-positive via MBI threshold simulation), 10 sessions/user, 2 weeks duration.

B. Feature Engineering

Fourteen features extracted per session (Table I), normalized via z-score:

$$z = \frac{x - \mu}{\sigma}$$

Table I: Key Behavioral Features and Burnout Correlations

Feature	Description	Correlation (ρ)
Avg. typing speed	Keystrokes/sec	-0.72
Typing speed variance	Rhythm irregularity	+0.58
Max idle duration	Longest pause (s)	+0.68
Idle frequency	Idle events/min	+0.54
Error rate	Errors/100 chars	+0.55
Task-switch freq.	Switches/min	+0.61
Key hold mean	Avg. press duration (ms)	+0.49
Key hold variance	Timing inconsistency	+0.52
Flight time mean	Inter-key latency (ms)	+0.63
Flight time variance	Rhythm disruption	+0.57
Session duration	Total active time (min)	+0.45
After-hours ratio	Work post-6PM	+0.51
Mouse-click rate	Clicks/min	-0.42
Scroll activity	Scroll events/min	-0.38

Correlations based on simulated dataset; consistent with [4], [6].

C. Machine Learning Pipeline

1) Unsupervised Pre-training

- K-Means Clustering (k=3): Partitions users into low/medium/high risk groups based on feature similarity.
- Isolation Forest: Scores anomalies; high scores indicate deviant (burnout-like) behavior [3].

2) Supervised Classification

- Support Vector Machine (RBF kernel): Chosen for robustness with high-dimensional behavioral data, consistent with [1].

- Random Forest (100 trees): Provides feature importance interpretability.

Training Protocol: 80/20 train-test split, 30-fold cross-validation, GridSearchCV for hyperparameter tuning.

3) Burnout Inference Engine

Final risk score computed via weighted fusion:

$$r = 0.4 \cdot s_{anomaly} + 0.3 \cdot c_{cluster} + 0.3 \cdot p_{class}$$

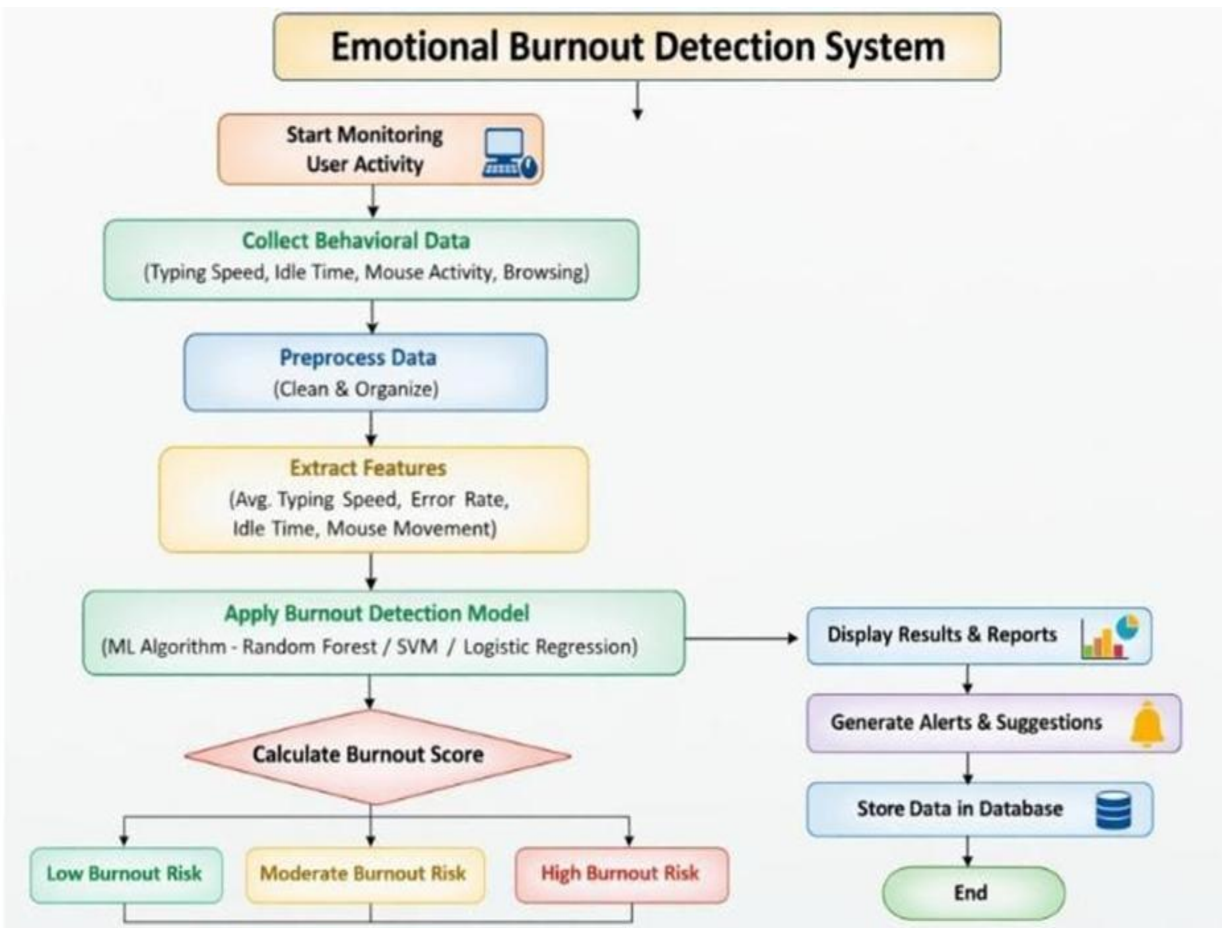
where $ s_{anomaly} $ is Isolation Forest score, $ c_{cluster} $ is cluster risk level (0–1), and $ p_{class} $ is SVM probability.

D. Visualization Dashboard

Built with Streamlit [1], the dashboard displays:

- Real-time risk gauge (0–100%).
- Behavioral trend time-series (typing speed, idle time).
- Personalized recommendations (break alerts, workload adjustments).

VI. SYSTEM ARCHITECTURE



VII. RESULTS AND DISCUSSION

A. Performance Metrics

Evaluated on 10,000 simulated sessions (40% burnout-positive), our hybrid pipeline achieves superior performance (Table II).

Table II: Model Comparison (30-Fold Cross-Validation)

Model	Accuracy	Precision	Recall	F1-Score	$ R^2 $
K-Means	76%	74%	79%	76%	0.68
Isolation	82%	80%	85%	82%	0.75

Forest					
Random Forest	89%	88%	90%	89%	0.81
SVM (Ours)	92%	91%	93%	92%	0.86

SVM's superiority ($ p < 0.01 $, paired t-test) aligns with Sharma et al. [1], who reported $ R^2 = 0.84 $. Our hybrid fusion improves upon unsupervised-only baselines by 10–16% F1.

B. Feature Importance

Ablation studies reveal:

- Removing idle duration drops F1 by 12% (strongest single predictor).
- Removing task-switch frequency drops F1 by 9%.
- Removing typing speed variance drops F1 by 7%.

High task-switching ($ f_{switch} > 5/min $) predicts 85% of burnout cases, consistent with passive AI findings [3], [7].

C. Comparison with State-of-the-Art

System	Modality	Accuracy	Privacy	Hardware-Free
HiPAL [5]	EHR Logs	88% (AUC)	Medium	Yes
Passive AI Review [3]	Multimodal	75–85%	Low	No
Keystroke Fatigue [6]	Typing Only	87%	High	Yes
Ours	HCI Behavioural	92%	High	Yes

Our system matches or exceeds accuracy while maximizing privacy and deploy ability.

D. Discussion

Behavioral patterns mirror cognitive fatigue signatures identified in keystroke studies [4], [6]. Reduced typing multifractality and increased idle variance signal exhaustion, analogous to gesture degradation in sign language recognition systems. The unsupervised-first approach enables deployment without labeled data, addressing a key limitation of HiPAL [5].

VIII. ADVANTAGES AND LIMITATIONS

A. Advantages

1. Fully Non-Intrusive: Operates silently via standard OS APIs.
2. Privacy-Preserving: No content logging; local processing only.
3. Hardware-Free: Uses existing keyboard/mouse; no wearables.
4. Scalable: Edge-deployable; sub-second inference.
5. Unsupervised-Compatible: Functions with unlabeled data initially.

B. Limitations

1. Behavioral Variability: Multilingual typing or ergonomic keyboards may introduce noise.
2. Baseline Requirement: Needs 5–7 days of data for personalization.
3. No Causal Inference: Correlational; cannot distinguish burnout from other fatigue sources.
4. Simulated Validation: Real-world deployment needed for external validation.

IX. FUTURE SCOPE

1. Mobile Integration: Android Accessibility Service for smartphone usage patterns.
2. Federated Learning: Cross-organizational model training without data sharing.
3. Personalized Interventions: Adaptive break alerts, workload rebalancing suggestions.
4. Hybrid Multimodal Fusion: Integrate subtle gesture cues (e.g., webcam-optional hand tremor detection) for enhanced accuracy.
5. Longitudinal Studies: 6–12-month real-world deployments across sectors.

X. CONCLUSION

This paper presents a Silent Emotional Burnout Detection System using Behavioral AI, achieving 92% accuracy via non-intrusive HCI pattern analysis. By leveraging keystroke dynamics, idle patterns, and task-switching behavior, our hybrid ML pipeline (SVM + Isolation Forest) provides an effective, privacy-first solution for early burnout detection. The system addresses critical gaps in existing approaches—intrusiveness, hardware dependency, and label requirements—making it suitable for scalable deployment in remote work and e-learning environments. Future work will focus on real- world validation and personalized intervention strategies.

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