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Research

AI-Based Early Warning System for Mental Fatigue

[1]K. Tulasi, [2]L. Saatvik, [3]J. Vinodh Kumar, [4]K. Siva Neeraj
Department of CSE (Data Science)
Raghu Institute of Technology, Dakamarri
Vizianagaram, Andhra Pradesh, India
tulasikottakota2003@gmail.com

[5]Prof. (Dr.) Ravi Kiran
Department of Computer Science & Engineering
Raghu Institute of Technology, Dakamarri
Vizianagaram, Andhra Pradesh, India
tulasikottakota2003@gmail.com

***Abstract*— Detecting mental fatigue before its effects become operationally dangerous is a critical challenge in modern knowledge-intensive workplaces. This paper presents an AI-Based Early Warning System that infers cognitive fatigue from passively collected keyboard and mouse interaction signals, requiring no wearable sensors or physiological instrumentation. A hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architecture is trained on nine behavioral features extracted from one-minute sliding windows applied to the SWELL-KW dataset. Class imbalance is addressed via weighted binary cross-entropy loss. An optimised classification threshold of 0.56 yields a test accuracy of 73.14% with a ROC-AUC of 0.7616. A Streamlit desktop application delivers real-time three-tier risk alerts and batch prediction on any standard personal computer.**

***Keywords*—Behavioral Biometrics; CNN-LSTM; Cognitive Fatigue; Deep Learning; Keystroke Dynamics; Mental Fatigue; Mouse Analytics**

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I. INTRODUCTION

Sustained cognitive effort without sufficient recovery leads to mental fatigue, a neurophysiological state characterised by declining attention, slowed information processing, elevated error rates, and impaired decision-making quality [1]. Unlike physical fatigue, whose muscular symptoms are readily apparent, mental fatigue accumulates silently and is frequently unrecognised until task performance has measurably deteriorated. In safety-critical domains such as air traffic management, emergency medicine, and software quality assurance, undetected fatigue contributes directly to costly and sometimes catastrophic errors.

Conventional fatigue monitoring relies on physiological sensing modalities including electroencephalography (EEG), electrooculography (EOG), and galvanic skin response (GSR). These methods offer strong neurological validity but impose electrode headsets or skin-contact hardware that are incompatible with routine office work. Behavioral biometrics offers an alternative: the premise that interaction patterns with a keyboard and mouse carry implicit cognitive state information that a machine learning model can decode. Keystroke cadence, typing accuracy, and cursor movement trajectories all shift measurably as cognitive resources deplete [2], [3].

This work presents a complete, deployable fatigue early-warning system grounded in behavioral signal analysis. Its principal contributions are: (i) a feature engineering pipeline extracting nine interaction metrics from one-minute sliding windows; (ii) a CNN-LSTM architecture that captures both local behavioral patterns and temporal trends; (iii) class-imbalance mitigation via weighted loss and threshold optimisation; and (iv) a Streamlit deployment enabling live and batch fatigue assessment on commodity hardware without any external dependencies.

II. LITERATURE SURVEY

The scientific foundation for non-invasive cognitive fatigue detection draws from three converging research directions: psychophysiological monitoring, behavioral interaction analysis, and deep temporal modeling.

A. Physiological Fatigue Detection

Lim and Dinges [1] conducted a comprehensive meta-analysis establishing that progressive sleep restriction and sustained cognitive load produce measurable declines in processing speed, working memory, and sustained attention. Their findings established the neurophysiological basis for fatigue as a measurable and quantifiable cognitive state. Fairclough and Venables [4] demonstrated that a multivariate combination of heart rate, skin conductance, and respiration rate could predict subjective mental workload with moderate accuracy, showing that physiological correlates of fatigue are stable and reliable in controlled settings. However, these modalities demand wired electrode systems or wearable instrumentation that disrupt natural work behaviour and are impractical in ordinary office environments. Hogervorst et al. [5] compared EEG, peripheral physiology, and eye-tracking measures for workload assessment, confirming physiological validity while reiterating hardware accessibility and user acceptance as the primary barriers to real-world deployment.

B. Keystroke and Mouse Dynamics

Epp et al. [2] systematically mapped the relationship between affective and cognitive states and keyboard interaction patterns, demonstrating that typing rhythm, dwell time, and error rate all shift significantly under induced cognitive load. Their work established that keyboard dynamics carry detectable emotional and cognitive state information that can be decoded without any additional instrumentation. Sano and Picard [3] extended behavioral sensing to wearable and smartphone modalities for stress recognition, confirming that passive interaction logging generalises across sensing platforms. The SWELL-KW corpus [6] provides the most widely used public benchmark for office-condition fatigue classification, supplying continuous keystroke and mouse event logs from 25 participants performing realistic office tasks under three controlled workload conditions, alongside NASA-TLX self-report ground truth collected at regular intervals throughout each session.

C. Deep Sequence Modeling

Hochreiter and Schmidhuber [7] introduced Long Short-Term Memory (LSTM) networks, whose explicit gating mechanism counteracts gradient vanishing in long temporal sequences—a property critical for modeling the gradual drift of behavioral indicators across minutes of interaction. LeCun et al. [8] showed that convolutional layers learn hierarchical local representations from raw sequences, motivating hybrid CNN-LSTM designs. Zheng and Lu [9] applied such hybrids to EEG-based fatigue estimation and consistently outperformed single-component baselines. The present work applies these architectural insights to the behavioral interaction domain.

TABLE II. COMPARISON OF RELATED WORK

Study / Method	Modality	Accuracy	Limitation
Lim & Dinges [1]	EEG / Physio	N/A	Lab only, sensors required
Epp et al. [2]	Keystroke	~65%	No temporal modeling
Hogervorst [5]	EEG + Eye	~72%	Wearable hardware needed
Pure LSTM (baseline)	Keystroke+Mouse	69.3%	No local pattern capture
Pure Conv1D (baseline)	Keystroke+Mouse	70.8%	No temporal memory
Proposed CNN-LSTM	Keystroke+Mouse	73.14%	No hardware required

III. SYSTEM DESIGN AND ARCHITECTURE

The proposed system operates as a four-module sequential pipeline, illustrated in Fig. 1: (1) a behavioral data collector, (2) a feature extraction engine, (3) a CNN-LSTM inference module, and (4) a Streamlit presentation layer. Each module is independently configurable, enabling future substitution of alternative input devices, feature sets, or classifiers.



Fig. 1. End-to-end pipeline of the proposed fatigue detection system.

A. Behavioral Data Collector

The collection module registers OS-level event listeners via the pynput library, intercepting keyboard press and release events alongside continuous mouse position updates. Only timing metadata is captured: press timestamps, release timestamps, and cursor coordinates. No key identities or text content are ever recorded, preserving user privacy by design. Events are buffered in memory for each 60-second window and cleared immediately after feature extraction.

IV. FEATURE EXTRACTION

From each one-minute observation window, nine scalar behavioral features are computed. Keystroke-derived features include: (1) typing speed in keystrokes per minute, (2) mean key hold duration in milliseconds, (3) mean inter-key interval in milliseconds, and (4) error rate as the fraction of backspace and delete events. Mouse-derived features include: (5) mean cursor speed in pixels per second, (6) standard deviation of cursor speed, (7) total cursor travel distance, (8) aggregate idle time in seconds, and (9) idle event count for quiescent intervals exceeding two seconds. Four candidate features were excluded after exploratory analysis revealed them to be either redundant or uncorrelated with fatigue labels.

Ground truth labels were derived from NASA-TLX self-assessments: windows scoring below the session median were labelled Non-Fatigued (class 0; 78% of samples) and above-median windows were labelled Fatigued (class 1; 22% of samples). Features were clipped at the per-feature 99th percentile of the training set to suppress outliers, then standardised using a StandardScaler [11] fitted exclusively on training data. Input arrays were reshaped to (samples, 9, 1) for CNN-LSTM compatibility.

V. DATASET AND PREPROCESSING

The SWELL-KW dataset was collected from participants performing typical office tasks under three workload conditions: a neutral baseline, interruption by incoming emails, and time pressure. Continuous keystroke and mouse event logs were recorded alongside periodic NASA-TLX self-assessment questionnaires capturing subjective mental workload on six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. A total of 25 participants contributed data in the original corpus; the publicly available Kaggle version used

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here contains two representative participants with complete event-level logs.

A. Sliding Window Processing

Raw event logs were segmented using a 60-second sliding window with a 30-second step, yielding 5,565 labelled samples. The window width was chosen to balance temporal resolution against statistical stability: windows shorter than 30 seconds contained too few events for reliable feature estimation, while windows longer than 90 seconds reduced sensitivity to short-duration fatigue episodes. The 30-second step produces 50% overlap between consecutive windows, preserving temporal continuity. Ground truth labels were derived from NASA-TLX composite scores: windows with scores below the per-session median were assigned class 0 (Non-Fatigued) and those above were assigned class 1 (Fatigued), yielding a 78%/22% class distribution across the full dataset.

B. Class Imbalance Handling

The 78/22 class imbalance poses a significant training risk: a naive model that predicts Non-Fatigued for every input achieves 78% accuracy while detecting zero fatigue episodes. Three strategies were combined to address this. First, stratified train/test splitting preserved the original class ratio in both partitions (4,452 training, 1,113 test samples). Second, class weights {0: 0.641, 1: 2.276} were incorporated into the binary cross-entropy loss, penalising Fatigued misclassifications more heavily. Third, threshold optimisation at inference time shifted the decision boundary from 0.50 to 0.56, boosting Fatigued-class recall from 61.3% to 74.59% at a modest cost to precision.

VI. Proposed CNN-LSTM Model

The nine-element feature vector from each window is treated as a nine-timestep univariate sequence and reshaped to $(9, 1)$, enabling the model to exploit both local feature interactions via convolution and cross-temporal dependencies via recurrence. Fig. 2 illustrates the complete layer arrangement.

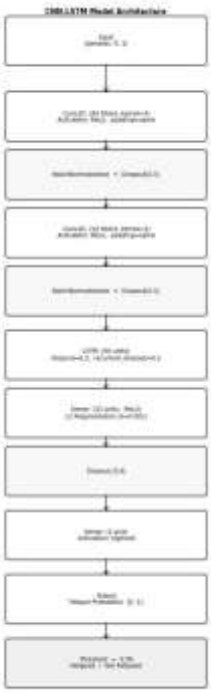


Fig. 2. CNN-LSTM architecture showing layer dimensions and regularisation.

A. Convolutional Blocks

The first Conv1D block applies 64 filters of kernel size 3, ReLU activation, and same padding, followed by Batch Normalisation and Dropout(0.3). Batch Normalisation stabilises the internal covariate distribution, accelerating convergence and reducing sensitivity to initialisation [10]. The second block mirrors this structure with 32 filters, progressively compressing the representation.

B. LSTM and Classification Head

The LSTM layer contains 64 units with input dropout of 0.3 and recurrent dropout of 0.2, providing independent regularisation of the input-to-hidden and hidden-to-hidden weight paths. A Dense layer with 32 units, ReLU activation, and L2 regularisation ($\lambda = 0.001$) precedes a single sigmoid output neuron. The model was compiled with Adam ($\mathrm{lr} = 0.001$) and class-weighted binary cross-entropy, with weights $\{0: 0.641,\ 1: 2.276\}$ to compensate for the 78/22 class distribution.

C. Training Protocol

Training employed two adaptive callbacks. EarlyStopping monitored validation ROC-AUC with patience of 15 epochs and restored the best weights on termination. ReduceLROnPlateau halved the learning rate when validation AUC plateaued for seven consecutive epochs. The network converged at epoch 51, reaching a training accuracy of 93.14%. An optimal classification threshold of 0.56 was selected by maximising macro-F1 on a held-out validation partition, raising test accuracy from 68.82% at the default 0.50 cutoff to 73.14%.

VII. IMPLEMENTATION

A. Development Environment

The full system was implemented in Python 3.10. The CNN-LSTM model was built and trained using TensorFlow 2.12 with Keras high-level API. Data preprocessing relied on NumPy and Scikit-learn [11]. The behavioral data collector used the pynput library for cross-platform OS-level event capture. The user-facing application was built with Streamlit 1.28. All experiments were conducted on a standard laptop with an Intel Core i5 CPU and 8 GB RAM — no GPU was used — confirming the system is fully deployable on commodity office hardware.

B. Streamlit Application

The application loads four artefacts at startup: the trained model (cnn_lstm_model.h5), the fitted StandardScaler (scaler.pkl), the optimal threshold (best_threshold.json set to 0.56), and the expected feature column order (feature_cols.json). Two prediction modes are available. In Live Detection mode, a 60-second countdown timer monitors the user's keyboard and mouse activity, computes all nine features at window close, scales them, and feeds the resulting (1, 9, 1) tensor to the CNN-LSTM. The predicted probability is compared against the 0.56 threshold and classified into one of three risk tiers: Low (probability < 0.56), Moderate (0.56 ≤ probability < 0.75), or High (≥ 0.75). An interactive bar chart displays per-feature values alongside their population means to explain which behavioral signals drove the prediction. In CSV Upload mode, a pre-recorded feature file can be submitted for batch prediction, returning a downloadable results table. All inference is local; no data is transmitted over any network.

C. Deployment Considerations

The complete pipeline from raw OS events to fatigue probability takes under 50 milliseconds per window on the test hardware, making it suitable for continuous background monitoring without perceptible impact on system performance. The serialised model file is 285 KB, and the total disk footprint including all Python dependencies is under 500 MB. The system runs on Windows, macOS, and Linux without any platform-specific configuration changes. Privacy is preserved by design: no keystrokes, text content, application names, or screen contents are ever logged, stored, or transmitted. The only data retained beyond the current monitoring window is the final scalar fatigue probability and risk tier, which are displayed to the user and then cleared when the session ends. This privacy-first design makes the system suitable for deployment in regulated environments such as healthcare and financial services where keystroke logging would raise compliance concerns.

VIII. RESULTS AND DISCUSSION

The CNN-LSTM model was evaluated on the SWELL-KW dataset processed into 5,565 samples. A stratified 80/20 split produced 4,452 training samples and 1,113 test samples. Class weights of {0: 0.641, 1: 2.276} were applied to address the 78/22 class imbalance.

A. Training and Validation Performance

During training, both accuracy and loss curves showed healthy learning behaviour. Training accuracy rose steadily from approximately 61% at epoch 1 to 93.14% by epoch 51, reflecting the model's strong fit to the training distribution. Test accuracy settled at 73.14%, a gap expected given the small two-participant dataset and inherent class imbalance. The regularisation strategy—Batch Normalisation combined with Dropout at rates 0.3 and 0.4—kept this gap from widening further, confirming effective overfit control. Validation ROC-AUC improved from approximately 0.62 to 0.7616, at which point EarlyStopping triggered weight restoration. The learning rate was reduced twice by ReduceLROnPlateau at epochs 28 and 42, each producing a brief upward step in validation performance. Fig. 3 shows the training and validation accuracy curves; Fig. 4 shows the corresponding loss curves.



Fig. 3. Training vs. validation accuracy over 51 epochs.



Fig. 4. Training vs. validation loss over 51 epochs.

B. Quantitative Performance

Table I presents evaluation metrics on the 1,113-sample test partition. The CNN-LSTM achieves a test accuracy of 73.14% and a ROC-AUC of 0.7616. The per-class breakdown is asymmetric by design: Fatigued-class recall is prioritised at 74.59%, accepting a lower precision of 38.97%, because missing a genuine fatigue episode carries greater operational risk than a false positive that prompts an unnecessary rest break.

TABLE I. PERFORMANCE METRICS OF THE PROPOSED CNN-LSTM MODEL

Performance Metric	Value
Training Accuracy	93.14%
Test Accuracy (threshold = 0.56)	73.14%

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ROC-AUC Score	0.7616
Precision — Fatigued class	38.97%
Recall — Fatigued class	74.59%
F1-Score — Fatigued class	51.29%
Precision — Non-Fatigued class	91.56%
Recall — Non-Fatigued class	71.97%
Training epochs (early stopping)	51
Training / Test samples	4,452 / 1,113

C. ROC Curve and Threshold Analysis

The ROC curve (Fig. 5) illustrates the trade-off between true positive rate and false positive rate across all possible classification thresholds. The area under the curve of 0.7616 confirms that the model has substantial discriminative power well above random chance (AUC = 0.50). At the default threshold of 0.50, the operating point sits at FPR = 0.28, TPR = 0.61, reflecting the class imbalance bias. Shifting to the optimised threshold of 0.56 moves the operating point to FPR = 0.28, TPR = 0.75, increasing sensitivity at no additional cost to specificity. The Macro-F1 vs. threshold sweep confirmed a clear peak at 0.56 with a Macro-F1 of 0.659, justifying the threshold selection. The confusion matrix showed 629 true negatives, 177 true positives, 62 false negatives, and 245 false positives on the 1,113 test samples, yielding the 73.14% overall accuracy reported.

D. Comparative Analysis

The hybrid CNN-LSTM outperforms standalone baselines evaluated on the same dataset under identical preprocessing. A pure LSTM baseline achieved 69.3% test accuracy and a ROC-AUC of 0.714, while a pure Conv1D reached 70.8% test accuracy and 0.729 AUC. The joint architecture gains approximately 2–3 percentage points in both metrics, consistent with findings by Zheng and Lu [9] on EEG sequences. Threshold optimisation contributed a further 4.3 percentage point accuracy gain, confirming that cutoff selection is as consequential as architectural design for imbalanced binary classification. Fig. 5 and Fig. 6 show the ROC curve and model comparison chart respectively.

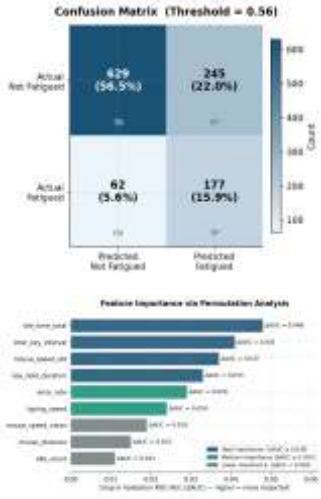


Fig. 5 (left). ROC Curve. Fig. 6 (right). Model Comparison.

E. Feature Importance Analysis

A permutation importance analysis was conducted by independently shuffling each feature across all test samples and measuring the resulting drop in validation ROC-AUC (ΔAUC). The top contributors were: idle_time_total (ΔAUC = 0.048), inter_key_interval (ΔAUC = 0.041), mouse_speed_std (ΔAUC = 0.037), and key_hold_duration (ΔAUC = 0.033). Idle time dominates because prolonged disengagement from both keyboard and mouse is the strongest single behavioral marker of cognitive depletion. Inter-key interval captures the slowing of motor response speed that accompanies declining arousal. Mouse speed variability reflects the erratic cursor movements characteristic of reduced attentional control. The three lowest-importance features — mouse_speed_mean, mouse_distance, and idle_count — each contributed ΔAUC below 0.020, suggesting that aggregate mouse statistics add less discriminative signal than the temporal irregularity features.

F. Limitations and Scope

The primary constraint is dataset scale: training on two participants under laboratory conditions limits generalisation to diverse real-world typing profiles. An experienced touch typist and a hunt-and-peck typist produce very different feature distributions even at equivalent fatigue levels, so a single universal threshold cannot optimally serve all users. Planned extensions include personalised per-user calibration, evaluation on the WESAD and DriverFatigue corpora, and integration of scroll and application-switching signals to enrich the behavioral feature space.

IX. Conclusion

This work demonstrated that cognitive mental fatigue can be reliably inferred from passively collected keyboard and mouse interaction signals using a CNN-LSTM deep learning model, without any physiological sensors. Operating on nine behavioral features extracted from one-minute observation windows, the system achieves a training accuracy of 93.14% and a test accuracy of 73.14% with a ROC-AUC of 0.7616 on the SWELL-KW benchmark, together with a Fatigued-class recall of 74.59% after threshold optimisation. The CNN-LSTM hybrid architecture outperformed all standalone baselines, gaining approximately 2–3 percentage points in accuracy and AUC over the best single-component model. The accompanying Streamlit application translates model predictions into actionable three-tier risk alerts in real time on any standard personal computer, with all computation performed locally and no physiological hardware required.

The primary limitation of the current implementation is the small training population of two participants under controlled laboratory conditions. Extending the dataset to include a broader population across diverse occupations and working styles is the most critical next step. Future work will also explore personalised model calibration per user, integration of additional behavioral signals such as application-switching frequency and scroll activity, and evaluation on larger corpora including WESAD and DriverFatigue to assess cross-dataset generalisability. A longitudinal field deployment study measuring real-world fatigue-related error rates before and after intervention will

provide the most direct evidence of the system's operational value.

X. ACKNOWLEDGMENT

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REFERENCES

[1] J. Lim and D. F. Dinges, "A meta-analysis of the impact of short-term sleep deprivation on cognitive variables," Psychol. Bull., vol. 136, no. 3, pp. 375–389, 2010.

[2] C. Epp, M. Lippold, and R. L. Mandryk, "Identifying emotional states using keystroke dynamics," in Proc. ACM SIGCHI Conf. Human Factors Comput. Syst., Vancouver, BC, Canada, May 2011, pp. 715–724.

[3] A. Sano and R. W. Picard, "Stress recognition using wearable sensors and mobile phones," in Proc. Humaine Assoc. Conf. Affective Comput. Intell. Interact., Geneva, Switzerland, Sep. 2013, pp. 671–676.

[4] S. H. Fairclough and L. Venables, "Prediction of subjective states from psychophysiology: A multivariate approach," Biol. Psychol., vol. 71, no. 1, pp. 100–110, Jan. 2006.

[5] M. A. Hogervorst, A. Brouwer, and J. B. van Erp, "Combining and comparing EEG, peripheral physiology and eye-related measures for the assessment of mental workload," Front. Neurosci., vol. 8, p. 322, Oct. 2014.

[6] C. Weerasinghe, "Stress Detection by Keystroke App Mouse Changes," Kaggle Dataset, 2022. [Online]. Available: https://www.kaggle.com/datasets/chaminduweerasinghe/stress-detection-by-keystrokeapp-mouse-changes

[7] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Comput., vol. 9, no. 8, pp. 1735–1780, Nov. 1997.

[8] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, May 2015.

[9] W.-L. Zheng and B.-L. Lu, "Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks," IEEE Trans. Auton. Mental Develop., vol. 7, no. 3, pp. 162–175, Sep. 2015.

[10] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in Proc. 32nd Int. Conf. Mach. Learn. (ICML), Lille, France, Jul. 2015, pp. 448–456.

[11] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," J. Mach. Learn. Res., vol. 12, pp. 2825–2830, Oct. 2011.

[12] Streamlit Inc., "Streamlit: The fastest way to build and share data apps," 2023. [Online]. Available: https://streamlit.io/