Journal of Computer and Electrical Sciences (JCES)- Volume-1 Issue-4, April 2026
ISSN: 3049-2602

SMARTPDF: MENTEL STRESS DETECTION USING SMARTPHONE SENSORS

R. AKIRA NANDAN NAIK
Under The Guidance of **Y. PRAKASH RAO**
Department of computer science engineering
Andhra Loyola institute of engineering and technology, Vijayawada, NTR dist., Andhra Predesh, India
Email id: naik27771@gmail.com

ABSTRACT

The increasing prevalence of psychological stress in modern society necessitates ubiquitous and non-invasive monitoring solutions. Conventional clinical assessments are often periodic and subjective. This paper proposes a real-time mental stress detection framework that leverages the inherent capabilities of modern smartphone sensors. By analysing data from accelerometers, gyroscopes, and light sensors, the system identifies behavioural patterns indicative of stress. Our approach utilizes a combination of signal processing for feature extraction and Machine Learning (ML) algorithms for classification. Experimental results demonstrate that the proposed system achieves high accuracy in distinguishing between "stressed" and "relaxed" states, providing a scalable tool for personalized mental health monitoring, The rapid escalation of mental health challenges in the digital age necessitates non-invasive, continuous monitoring systems. Traditional clinical diagnostics often rely on self- reporting, which is subjective and periodic. This paper proposes an AI-driven framework for mental stress detection utilizing ubiquitous smartphone sensors, including accelerometers, gyroscopes, and ambient light sensors. By leveraging Machine Learning (ML) algorithms, the system identifies behavioral markers and physiological proxies indicative of stress. Our methodology involves a robust data ingestion pipeline, feature engineering from time-series sensor data, and classification using Random Forest and Support Vector Machine (SVM) models. Experimental results indicate a classification accuracy of 89.2%, demonstrating the feasibility of using passive mobile sensing for real-time mental health intervention

Keywords: Mental Stress Detection, Smartphone Sensors, Machine Learning, AI C ML, Human Activity Recognition, Affective Computing.

1. INTRODUCTION

Mental stress has become a global health concern, linked to numerous physical and psychological ailments. While smartphones have historically been seen as a source of stress, they also serve as powerful diagnostic tools due to their array of built-in sensors. Modern devices can track movement, ambient environment, and usage patterns without requiring specialized medical hardware.This project introduces an AI-drive approach to detect stress levels by monitoring physical activity and environmental triggers via smartphone sensors. By treating stress detection as a classification problem within the AI C ML domain, we aim to provide users with actionable insights into their mental well-being.

https://doi.org/10.5281/zenodo.19610776

Unlike wearable medical devices, smartphone sensors—such as the accelerometer and gyroscope—provide a "frictionless" way to capture data without user intervention. This project aims to bridge the gap between AI and mental health by developing a system that can detect stress levels based on movement patterns and environmental context. By applying ML models to raw sensor data, we can provide users with early warnings and personalized stress-management insights.

2. LITERATURE SURVE

Research in "Affective Computing" has traditionally relied on wearable physiological sensors (e.g., ECG, GSR). However, recent studies have shifted toward "passive sensing" using mobile devices.

Activity-Based Detection: Researchers have found that changes in gait and physical activity levels, captured by accelerometers, correlate strongly with high-cortisol periods.

Environmental Context: Ambient light and noise levels provided by smartphone sensors offer context regarding the user's environment, which acts as a stressor or a relaxant.

ML Paradigms: Previous models using Support Vector Machines (SVM) and Random Forests have shown promise, but Deep Learning approaches like Long Short-Term Memory (LSTM) networks are increasingly used to handle the temporal nature of sensor data.

3. PROPOSED METHODOLOGY

The methodology follows a standard AI C ML pipeline tailored for mobile sensor data. The proposed system architecture is divided into four distinct phases

3.1 Data Acquisition
Data is collected from three primary sensors:

Accelerometer: Captures physical agitation or lethargyGyroscope: Detects orientation changes during phone usage.
Light Sensor: Measures environmental brightness to infer indoor/outdoor context.

3.2 Preprocessing and Feature Extraction
Raw sensor data is noisy. We apply a Butterworth low-pass filter to remove high- frequency noise. Features such as Mean, Standard Deviation, and Spectral Entropy are extracted from 10-second sliding windows with a 50% overlap.
3.3 Model Architecture
We employ a Random Forest Classifier and a Neural Network (MLP) for stress classification. The model categorizes the state into three levels: Low, Medium, and High Stress.
3.4 Classification Layer: The processed features are fed into a Random Forest Classifier. The model is trained to categorize states into 'Relaxed,' 'Anxious,' and 'Highly Stressed.

https://doi.org/10.5281/zenodo.19610776

4. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The Mental Stress Detection system is organized into three tiers: a presentation layer, an application logic layer, and a data processing layer. This layered architecture ensures modularity, scalability, and efficient system performance. Each layer operates independently, allowing easy updates, maintenance, and integration of new features without affecting the overall system.

4.1 Presentation Layer

The frontend is implemented as a mobile application (Android/iOS) or a responsive web application compatible with smartphones. The interface provides real-time visualization of stress levels, user activity monitoring, and alerts.

The application collects data from built-in smartphone sensors such as accelerometer, gyroscope, GPS, and optionally microphone and wearable-integrated heart rate sensors. The UI displays stress insights using graphs, charts, and notifications.

Technologies such as Flutter/React Native (for mobile apps) or React.js (for web apps) can be used for building a responsive and interactive interface. The system also supports user input for feedback and manual stress level logging.

4.2 Application Logic Layer

The backend is implemented using Python with frameworks such as FastAPI or Flask, chosen for their efficiency in handling asynchronous requests and real-time data processing.

The application exposes key API endpoints:

POST /sensor-data – for uploading real-time sensor data POST

/predict – for stress level prediction

GET /history – for retrieving past stress records

Data processing tasks such as feature extraction and model inference are handled within this layer. Machine learning models like Support Vector Machine (SVM), Random Forest, or Deep Learning models (LSTM) are used to analyze behavioral patterns and predict stress levels.

Background processing is managed using task queues (e.g., Celery) to handle continuous data streams without affecting system responsiveness.

4.3 Data Processing Layer

The data layer manages storage, preprocessing, and analysis of sensor data. It includes: Database:

Stores user data, sensor logs, and stress history (PostgreSQL or MongoDB) Caching System:

Redis for fast data retrieval and session handling

Data Processing Module:

Noise filtering and normalization

Time-series segmentation

https://doi.org/10.5281/zenodo.19610776

Feature extraction (activity level, sleep patterns, phone usage behavior)

Machine learning models are trained using historical labeled datasets and deployed for real-time inference. The system may also use cloud storage for scalability and backup.

The entire system can be containerized using Docker, enabling smooth deployment across cloud platforms and local environments. This ensures reliability, scalability, and easy maintenance.

EXPERIMENTAL RESULTS AND ANALYSIS

System performance was evaluated across three experimental dimensions: stress detection accuracy, sensor data processing latency, and comparative benchmarking against existing stress detection approaches. All experiments were conducted on a mid-range smartphone (Android device with 8 GB RAM, Octa-core CPU) without external wearable devices, ensuring realistic real-world deployment conditions.

4.4 Evaluation Dataset and Metrics

A curated dataset of 800 labelled instances was collected from 50 participants over a period of 2 weeks using smartphone sensors such as:

* Accelerometer
* Gyroscope
* GPS
* Screen usage logs
* Call C app activity patterns

Stress levels were categorized into three classes:

* Low Stress
* Moderate Stress
* High Stress

Ground-truth labels were obtained through:

* Self-reported surveys (Perceived Stress Scale - PSS)
* Daily mood logging

Inter-annotator agreement (between survey consistency and behavioral patterns) achieved a Cohen's Kappa score of 0.81, indicating strong reliability.

Evaluation Metrics

Performance was assessed using:

https://doi.org/10.5281/zenodo.19610776

* Accuracy
* Precision
* Recall
* F1-Score

Additionally:

* Confusion Matrix analysis for classification performance
* ROC-AUC for model robustness

4.5 Model Performance Comparison

Table I presents a comparative analysis of stress detection performance across four configurations:

* Random Forest (baseline)
* Support Vector Machine (SVM)
* LSTM (deep learning model)
* Proposed Hybrid Model (Sensor Fusion + LSTM)

TABLE I. STRESS DETECTION PERFORMANCE ACROSS MODELS

MODEL/ APPROACH	ACCURACY (%)	PRECISION (%)	RECALL (%)	F1-SCHORE (%)
Random forest	82.4	81.2	80.5	80.8
SVM	84.7	83.6	82.9	83.2
LSTM	90.3	89.7	88.9	89.3
Proposed model	93.8	92.9	93.5	93.2

The proposed system achieves the highest performance across all metrics, demonstrating the effectiveness of combining sensor fusion with temporal deep learning models.

* Traditional ML models struggle with temporal dependencies.
* LSTM improves sequence understanding but lacks multi-sensor optimization.
* The hybrid model leverages both context-awareness and temporal patterns, leading to superior results.

4.6 Sensor Contribution Analysis

To understand the importance of each sensor, an ablation study was conducted.

Key Observations:

Screen usage C app activity → strongest indicators of stress

Accelerometer data → useful for detecting physical inactivity/restlessness GPS

data→ identifies routine disruption patterns

Gyroscope→ minor contribution

Removing any major sensor reduced accuracy by 3–7%, confirming the importance of multi-sensor fusion

https://doi.org/10.5281/zenodo.19610776

4.7 Query Response Time Analysis

Table II reports processing latency across different data window sizes.

TABLE II. PROCESSING LATENCY ACROSS DATA WINDOWS

DATA WINDOW SIZE	SAMPLES	FEATURE EXTRACTION (S)	PREDICTION TIME(S)	TOTAL TIME(S)
Small	1-100	0.5	0.3	0.8
Medium	100-500	1.4	0.6	2.0
Large	500-1000	3.2	1.1	4.3
Very Large	1000+	6.8	1.9	8.7

Insights:

* Feature extraction scales linearly with data size

* Prediction time remains relatively stable due to optimized model inference

* Real-time stress detection (<2 seconds) is achievable for most practical scenarios

4.8 Comparative System Analysis

Table III compares the proposed system with existing stress detection approaches.

TABLE III. COMPARATIVE ANALYSIS OF STRESS DETECTION SYSTEMS

SYSTEM	SENSORS USED	REAL-TIME DETECTION	ML MODEL	ACCURACY	SCALABLE
Wearable based	Heart Rate	Yes	SVM	85%	No
App Usage Tracker	Screen Data	Partial	RF	80%	Yes
Hybrid Research Model	Multiple Sensors	No	LSTM	89%	No
Proposed System	Multi-Sensor Fusion	Yes	Hybrid (LSTM)	93.8%	Yes

Key Advantages of Proposed System:

* No external hardware required

* Fully smartphone-based sensing

* Real-time stress detection

* High scalability and deployment feasibility

https://doi.org/10.5281/zenodo.19610776

5. CONCLUSION AND FUTURE SCOPE

This paper presented a smartphone-based mental stress detection system that leverages mult sensor data and machine learning techniques to enable continuous, real-time monitoring of user stress levels. By integrating behavioral signals such as physical activity, location patterns, screen usage, and app interaction logs, the proposed system provides a context-aware understanding of mental stress without requiring additional wearable devices.

The system architecture addresses key limitations of traditional stress detection approaches namely dependence on expensive physiological sensors and lack of real- time adaptability through a scalable and non-intrusive framework that utilizes widely available smartphone sensors. The hybrid model combining sensor fusion with temporal learning effectively captures both short-term variations and long-term behavioral patterns associated with stress.

Experimental results demonstrate that the proposed system achieves an accuracy of 93.8% in classifying stress levels, outperforming conventional machine learning models and single-sensor approaches. The system maintains low latency, with real- time predictions achievable within practical time limits, making it suitable for everyday deployment. Furthermore, its lightweight design ensures compatibility with standard mobile devices without requiring specialized hardware.

Future research directions include enhancing the system's robustness through the incorporation of additional contextual signals such as sleep patterns, voice tone analysis, and social interaction metrics. The integration of advanced deep learning models, such as transformer-based architectures, could further improve predictive performance and personalization.

Additionally, expanding the system to support cross-device integration with wearables (e.g., smartwatches) can provide richer physiological insights such as heart rate variability. Privacy-preserving techniques, including on-device processing and federated learning, will be explored to ensure secure handling of sensitive user data.

REFERENCES

1. Lane, N. D., Mohammod, M., Lin, M., Yang, X., Lu, H., Ali, S., Doryab, A., Berke, E., Choudhury, T., and Campbell, A. T., "BeWell: A Smartphone Application to Monitor, Model and Promote Wellbeing," Proceedings of the 5th International ICST Conference on Pervasive Computing Technologies for Healthcare, 2011, pp. 23–26.

2. Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., and Campbell, A. T., "StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones," Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computin, 2014, pp. 3–14.

https://doi.org/10.5281/zenodo.19610776

3. Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., and Mohr, D. C., "Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily- Life Behavior: An Exploratory Study," Journal of Medical Internet Research, vol. 17, no. 7, 2015.

4. Gjoreski, M., Gjoreski, H., Lutrek, M., and Gams, M., "Continuous Stress Detection Using a Wrist Device: In Laboratory and Real Life," Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing, 2016, pp. 1185–1193.

5. Sano, A. and Picard, R. W., "Stress Recognition Using Wearable Sensors and Mobile Phones," Proceedings of the IEEE International Conference on Affective Computing and Intelligent Interaction, 2013, pp. 671–676.

6. Healey, J. and Picard, R. W., "Detecting Stress During Real-World Driving Tasks Using Physiological Sensors," IEEE Transactions on Intelligent Transportation Systems, vol. 6, no. 2, 2005, pp. 156–166.

7. Lu, H., Frauendorfer, D., Rabbi, M., Mast, M. S., Chittaranjan, G. T., Campbell, A. T., Gatica-Perez, D., and Choudhury, T., "StressSense: Detecting Stress in Unconstrained Acoustic Environments Using Smartphones," Proceedings of the ACM International Conference on Ubiquitous Computing, 2012, pp. 351–360.

8. Bogomolov, A., Lepri, B., Ferron, M., Pianesi, F., and Pentland, A., "Daily Stress Recognition from Mobile Phone Data, Weather Conditions and Individual Traits," Proceedings of the ACM International Conference on Multimedia, 2014, pp. 477–486.

9. Canzian, L. and Musolesi, M., "Trajectories of Depression: Unobtrusive Monitoring of Depressive States by Means of Smartphone Mobility Traces Analysis," Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing, 2015, pp. 1293–1304.

10. Wahle, F., Kowatsch, T., Fleisch, E., Rufer, M., and Weidt, S., "Mobile Sensing and Support for People with Depression: A Pilot Trial in the Wild," JMIR mHealth and uHealth, vol. 4, no. 3, 2016.

https://doi.org/10.5281/zenodo.19610776