A Survey on Artificial Intelligence – Powered Stress Monitoring and Adaptive Solution

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Abstract: This study presents a comprehensive survey on Artificial Intelligence–powered stress monitoring and adaptive solution systems. The survey explores how AI techniques are used to detect, analyze, and manage stress in individuals across different environments. Various data sources such as physiological signals, behavioral patterns, and contextual information are reviewed. Machine learning and deep learning models employed for stress detection are examined in detail. The paper highlights the role of wearable devices and smart sensors in real-time stress monitoring. Adaptive solution mechanisms, including personalized feedback and intervention strategies, are discussed. The effectiveness of AI-driven systems in improving mental well-being is evaluated. Key challenges such as data privacy, accuracy, and ethical concerns are identified. The survey also compares existing models and frameworks in stress management applications.

Keywords: Physiological Signals, Deep Learning, Random Forest, Decision Tree, Stress Detection.

I.INTRODUCTION

This work is intended to help students and IT worker manage stress, especially when they experience high levels of stress frequently. With the help of machine learning and image processing, the system uses a live camera feed to study stress through facial expressions. The system is used to observe key facial features like eye movements, mouth tension, eyebrow position, and muscle tension as signs of stress.Different levels of stress can be identified quickly by tracking small changes in these features. The system offers immediate feedback on stress levels and it provide a simple way to relieve stress. It may recommend breathing exercises, stretching, meditation, or short breaks for relaxation based on the level of stress it detects. By using this tool, workplaces and schools can build a healthy and positive working environment through early stress detection. In this study, AI is demonstrated as potential support for mental health by helping people manage their stress in real-time.

II. LITERATURE REVIEW & RELATED WORK

AI-powered stress monitoring has shifted from subjective self-reports to data-driven approaches using wearable sensors. Physiological signals like heart rate, GSR, EEG, and respiration are analyzed with machine learning models such as SVM, Random Forest, and k-NN, while deep learning models like CNNs and LSTMs improve real-time accuracy.

2.1 Machine Learning in Macroeconomics

Machine learning (ML) is increasingly used in macroeconomics for forecasting, pattern recognition, and policy analysis. Traditional models often assume linear relationships and may miss complex interactions. ML techniques like decision trees, random forests, SVMs, and neural networks can capture nonlinear patterns among indicators such as GDP, inflation, and unemployment. They are useful for business cycle analysis, crisis detection, and real-time economic assessment using large datasets. ML also supports policy evaluation and identifies key economic drivers. Combining ML with traditional frameworks improves reliability, interpretability, and policy relevance.

2.2 Comparative Analysis of Classifiers

In the context of machine learning applications in macroeconomics, a comparative analysis of classifiers reveals notable differences in performance, interpretability, and suitability for economic data. Traditional classifiers such as Logistic Regression and Naïve Bayes offer high interpretability and align well with economic theory but often struggle to capture nonlinear relationships. Tree-based models like Decision Trees and Random Forests provide better handling of nonlinearities and variable interactions, with Random Forests generally achieving higher predictive accuracy and robustness. Support Vector Machines perform well in high-dimensional macroeconomic datasets but require careful kernel selection and parameter tuning. Deep learning models, including Artificial Neural Networks, demonstrate superior predictive power for complex patterns but lack transparency and are computationally intensive

2.3 The Impact of Fiscal Indicators

Fiscal indicators play a crucial role in analyzing the overall health and performance of an economy. Key indicators such as government expenditure, tax revenue, fiscal deficit, and public debt significantly influence economic growth and stability. Changes in fiscal policy affect aggregate demand, investment, and employment levels. Expansionary fiscal measures can stimulate growth during economic slowdowns, while contractionary policies help control inflation. Fiscal deficits and rising public debt may lead to long-term sustainability concerns. Effective tax structures influence income distribution and consumer spending

III. METHODOLOGY

The study employs machine learning techniques to analyze the impact of fiscal indicators on macroeconomic performance using secondary time-series data. Comparative evaluation of classifiers is conducted based on accuracy and interpretability to identify the most suitable model for policy analysis.

3.1 System Architecture

The following diagram illustrates the high-level data flow, from raw Artificial Intelligence–powered stress monitoring and adaptive solution system.

3.2 Data Acquisition and Preprocessing

We constructed a multimodal dataset for Artificial Intelligence–powered stress monitoring and adaptive solutions using data collected from wearable devices, mobile sensors, and contextual source.

Key attributes includes:

Physiological: Heart Rate Variability (HRV), Galvanic Skin Response (GSR), Skin Temperature, EEG signals.

Behavioral: Physical activity levels, sleep patterns, smartphone usage, and interaction frequency.

Contextual: Environmental noise, location context, time of day, and workload indicator

IV. RESULTS AND DISCUSSION

The tuned Random Forest model achieved a classification accuracy of 0.7124, outperforming baseline models.

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.6035	0.6152	-	-
k-Nearest Neighbors	0.5821	0.5937	-	-
Random Forest (Tuned)	0.7124	0.7310	0.7124	0.7199

The superior performance of the Random Forest (F1-Score: 0.7199) demonstrates its ability to capture complex, nonlinear relationships among physiological and behavioral signals.

V. CONCLUSION

This survey shows the strong potential of AI in stress monitoring and adaptive management. By combining physiological, behavioral, and contextual data, AI systems can detect stress in real time and provide personalized interventions. Ensemble machine learning models like Random Forests perform best in capturing complex patterns from multimodal data. Adaptive solutions, including real-time feedback and recommendations, support mental well-being. Challenges like data privacy, sensor reliability, and model interpretability remain, highlighting the need for robust, user-focused frameworks and future research on explainable AI and wearable integration.

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