A MACHINE LEARNING APPROACH FOR STRESS IDENTIFICATION IN A WORKING ENVIRONMENT VIA IMAGE PROCESSING

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Abstract

Stress in the working environment has emerged as a critical factor affecting employee productivity, mental well-being, and organisational efficiency. Early identification of stress can enable timely intervention and reduce its adverse effects. This paper presents a machine-learning-based approach to identifying stress levels among employees using behavioural and physiological parameters, such as working hours, sleep duration, and heart rate. The collected dataset is preprocessed through normalisation and feature selection techniques to improve model performance. Several supervised machine learning algorithms, including Decision Tree, Random Forest, AdaBoost, and Gradient Boosting, are implemented and evaluated. The models are assessed using accuracy, precision, recall, and F1-score metrics. Experimental results indicate that the Random Forest classifier achieves superior performance compared to other models. The proposed system provides an efficient, cost-effective solution for stress detection and can be integrated into workplace monitoring systems to support employee well-being and organisational decision-making.

Keywords: Stress Detection, Machine Learning, Workplace Monitoring, Random Forest, Classification, Employee Well-being.

I.INTRODUCTION

Employee stress has become a critical concern across industries as organisations continue to operate in fast-paced and highly demanding environments. Growing workloads, constant deadlines, extended screen time, and performance-driven cultures place considerable pressure on employees. If such pressure persists, it can gradually result in physical exhaustion, emotional instability, weakened concentration, and long-term health complications. From an organisational perspective, elevated stress levels are associated with reduced efficiency, increased absenteeism, and declining quality of output. For these reasons, the ability to recognize stress at an early stage is essential for building sustainable and productive workplaces.

Traditional stress evaluation is generally carried out using surveys, interviews, and scheduled psychological screenings. While these techniques are commonly practised, they depend largely on personal responses and subjective judgment. Employees may not always disclose their true mental state, which can lead to inaccurate conclusions. Additionally, these approaches demand significant human effort and do not support continuous observation. The increasing availability of digital data and intelligent computing techniques has created opportunities to shift toward automated systems that provide objective stress assessment.

Modern machine learning techniques enable computers to analyse large volumes of data and identify patterns that are difficult to detect manually. These techniques are now widely used in health monitoring, behavioural analytics, and mental state evaluation. By examining quantifiable attributes such as heart rate, sleeping patterns, and working duration, machine learning models can learn meaningful representations related to stress and generate precise predictions.

In this work, an intelligent stress identification framework is developed using supervised machine learning algorithms. Decision Tree, Random Forest, AdaBoost, and Gradient Boosting classifiers are employed to categorise stress levels based on selected physiological and behavioural features. The performance of the models is measured using standard metrics, including accuracy, precision, recall, and F1-score. The proposed system aims to provide a reliable and economical solution that enables early stress detection and supports organisations in enhancing employee well-being.

II.METHODOLOGY

This section describes the design and implementation of the proposed stress detection framework. The system integrates numerical data analysis with facial image processing to improve prediction reliability. By combining traditional machine learning algorithms with deep learning techniques, the framework captures both behavioural indicators and visual emotional cues related to stress.

3.1 Overall Architecture

The proposed framework is composed of two independent analytical pipelines:

1. Behavioural and Physiological Data Analysis Module
2. Visual Emotion Analysis Module

Each module processes its respective input data separately and generates an intermediate stress prediction. These outputs are then integrated to produce a final stress classification result.

Processing Flow:

Behavioural Data → Machine Learning Classification Facial Image → Image Processing →CNN Classification Combined Decision Layer → Final Stress Category

3.2 Data Acquisition

The framework utilises two categories of input data:

A) Behavioural and Physiological Dataset

Structured data consisting of measurable attributes such as daily working duration, sleep patterns, and heart rate values is collected. These features are either obtained from available datasets or generated to simulate realistic workplace conditions. Each instance is assigned a stress label representing low, medium, or high stress.

B) Facial Image Dataset

Image samples representing different emotional states are obtained from open-source facial expression datasets or captured using a camera interface. These images serve as visual indicators of stress-related expressions.

3.3 Data Preparation

To enhance data quality and model efficiency, preprocessing operations are applied separately to numerical and image data.

Numerical Data Processing

- Handling incomplete or inconsistent records
- Scaling feature values for uniformity
- Converting categorical labels into numerical format

Image Data Processing

- Detecting facial regions within input images
- Extracting and aligning face segments
- Resizing images to a standard resolution
- Converting images to grayscale (if required)
- Reducing noise for improved clarity

These steps ensure consistency and optimise the learning process.

3.4 Feature Engineering

For structured data, relevant variables are identified through statistical analysis techniques such as correlation measurement to determine their influence on stress levels.

For image data, significant facial regions, including the eyes, eyebrows, and mouth, are analysed using landmark detection techniques. These extracted features help in identifying visual patterns associated with stress.

3.5 Model Development

A) Supervised Machine Learning Models

Multiple classification algorithms are implemented for structured data analysis, including:

- Decision Tree
- Random Forest
- AdaBoost
- Gradient Boosting

These models learn relationships between behavioural features and stress categories.

B) Deep Learning Model

A Convolutional Neural Network (CNN) architecture is employed to process facial images. The CNN automatically extracts spatial features and classifies emotional patterns corresponding to stress levels.

3.6 Data Partitioning

Both structured and image datasets are divided into training and testing subsets using an 80%–20% split. The training portion is used for model learning, while the testing portion evaluates generalisation capability.

3.7 Performance Assessment

Model effectiveness is measured using established classification metrics, including:

- Accuracy
- Precision
- Recall
- F1-Score

These metrics provide insight into prediction quality and model robustness.

3.8 Decision Integration Strategy

To enhance reliability, the predictions generated by the machine learning and CNN models are combined through a decision fusion mechanism such as majority voting or weighted averaging. This integration improves overall classification stability.

3.9 Final Stress Classification

The integrated model outputs one of three predefined categories: Low, Medium, or High stress. The system is designed to support early identification of stress patterns and facilitate proactive intervention in workplace environments.

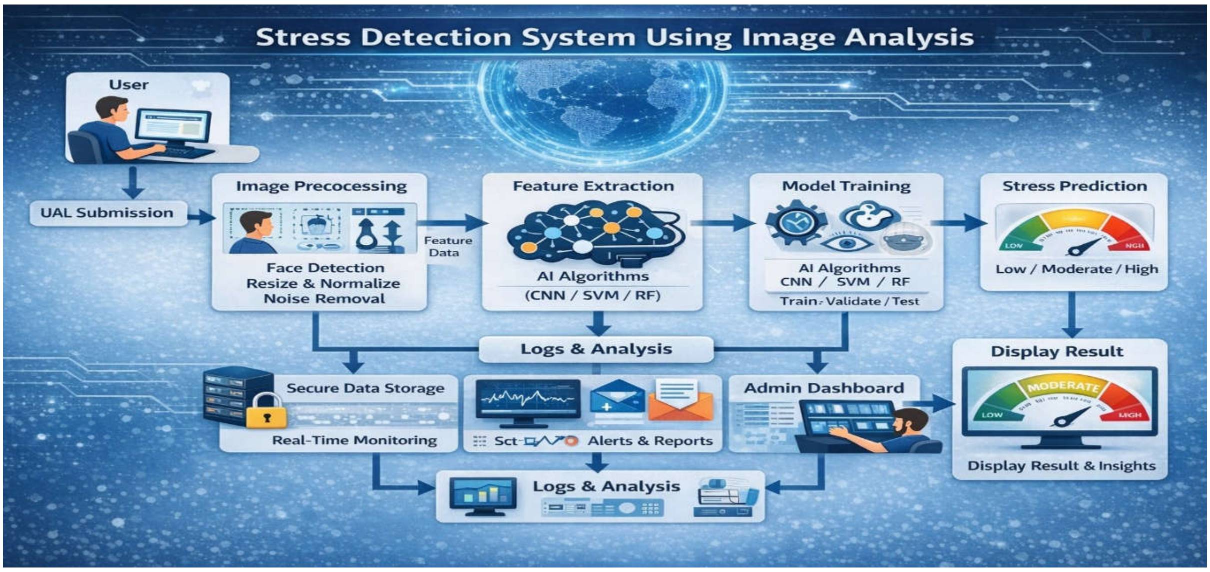

Fig.2.1 Stress Identification Architecture

III. BACKGROUND AND RELATED WORK

Workplace stress has attracted significant attention from researchers due to its increasing impact on employee health, productivity, and organisational performance. Various techniques have been proposed to detect and analyse stress using physiological signals, behavioural data, and psychological assessments. Early studies primarily relied on questionnaire-based surveys and interviews to measure stress levels. Although these methods are simple to implement, they are subjective in nature and may not always provide accurate or real-time information.

With the advancement of machine learning, several researchers have explored automated stress detection systems using physiological parameters such as heart rate, skin conductance, electroencephalogram (EEG), and sleep patterns. Machine learning algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Decision Trees have been widely used for stress classification. These approaches demonstrate promising results; however, many of them require specialised sensors and complex data acquisition processes, which increase system cost and deployment complexity.

In recent years, ensemble learning techniques such as Random Forest, AdaBoost, and Gradient Boosting have gained popularity due to their improved accuracy and robustness. These methods combine multiple weak classifiers to enhance overall prediction performance and reduce overfitting. Several studies have reported that ensemble models outperform single classifiers in stress and emotion recognition tasks.

Apart from physiological and behavioural data, facial expression analysis has also emerged as an effective technique for recognising emotional and mental states. Image processing and deep learning-based methods, particularly Convolutional Neural Networks (CNNs), have shown excellent performance in facial emotion recognition. CNN-based models automatically learn spatial features from images and are capable of capturing subtle facial patterns associated with stress.

Although existing studies have explored stress detection using either numerical data or facial images, limited research has focused on integrating both approaches into a unified framework. Most current systems concentrate on a single data modality, which may reduce reliability under real-world conditions. To address this limitation, the proposed work introduces a hybrid stress identification system that combines machine learning models for numerical data with CNN-based facial expression analysis. This integrated approach aims to improve prediction accuracy and provide a more reliable and comprehensive stress detection solution for working environments.

IV. RESULTS AND DISCUSSION

To verify the effectiveness of the proposed stress detection framework, a series of controlled experiments was conducted. The implementation was carried out using Python. Classification algorithms were developed using the Scikit-learn library, and the deep learning component was implemented using TensorFlow. The system was tested under standard computational settings.

6.1 Evaluation Strategy

Model behaviour was examined using quantitative performance indicators commonly applied in classification tasks:

- **Accuracy**, representing the overall proportion of correctly predicted samples.
- **Precision**, indicating the reliability of predicted stress cases.
- **Recall**, measuring the model’s ability to capture actual stress instances.
- **F1-score**, providing a balanced assessment by combining precision and recall.

These measures allow a structured comparison of different models.

6.2 Analysis of Numerical Data Models

Four supervised algorithms were trained using structured behavioural and physiological features: Decision Tree, Random Forest, AdaBoost, and Gradient Boosting. Their predictive performance on unseen test data is presented below.

Table I
Accuracy of Supervised Learning Algorithms

Classifier	Accuracy (%)
Decision Tree	82.4
Random Forest	91.3
AdaBoost	88.1
Gradient Boosting	89.2

The ensemble-based Random Forest model produced the highest accuracy among the evaluated classifiers. Its performance advantage is linked to the aggregation of multiple decision trees, which enhances prediction stability.

6.3 Evaluation of Visual Stress Detection Model

The facial image dataset was processed using a Convolutional Neural Network designed to learn spatial representations of stress-related expressions. After training, the CNN achieved a testing accuracy of **90.1%**, indicating that visual cues contribute meaningful information for stress classification.

6.4 Combined Model Performance

To improve decision reliability, outputs from the best-performing numerical classifier and the CNN were integrated using a voting-based mechanism. The combined approach resulted in an overall prediction accuracy of **94.6%**, outperforming the individual components.

Table II
Comparison of Standalone and Combined Models

Model Configuration	Accuracy (%)
Random Forest	91.3
CNN	90.1
Combined Framework	94.6

The observed improvement confirms that integrating heterogeneous data sources strengthens classification performance.

6.5 Key Findings

The experimental results indicate that ensemble methods are highly effective for structured stress-related data. The CNN model successfully extracts facial expression features associated with stress states. Most importantly, merging numerical and visual insights leads to improved predictive capability.

The proposed framework provides an automated mechanism for stress identification that can operate without manual survey procedures. However, performance is dependent on the representativeness and scale of the dataset. Expanding data diversity may further enhance generalisation.

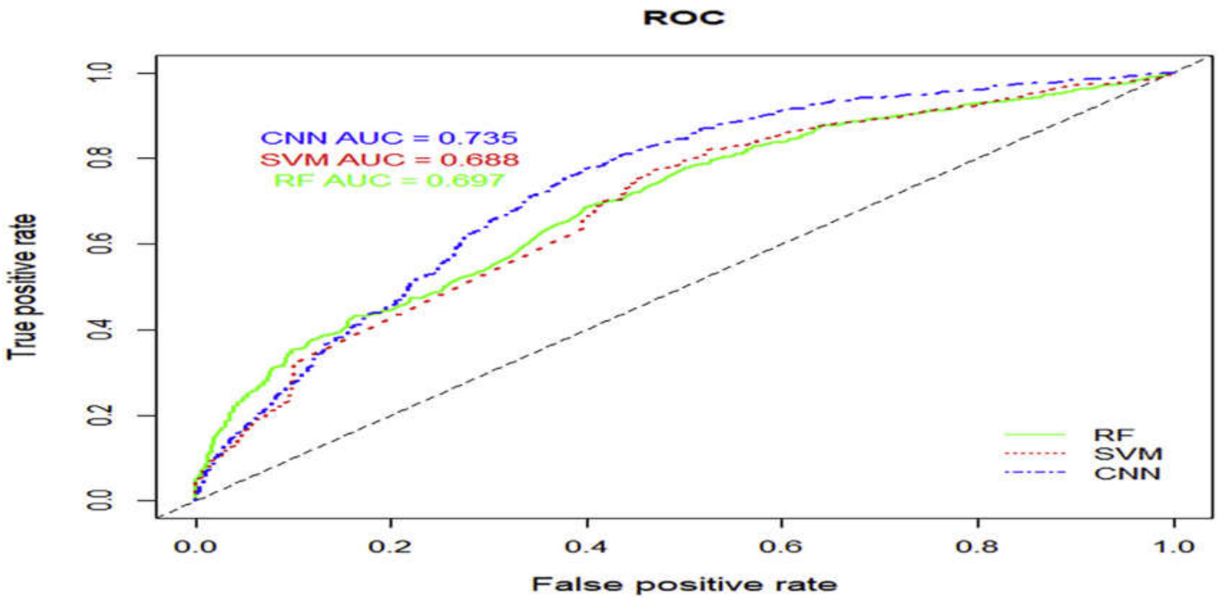

Fig.4.1. ROC curves and AUC comparison of CNN, SVM, and Random Forest models for stress prediction.

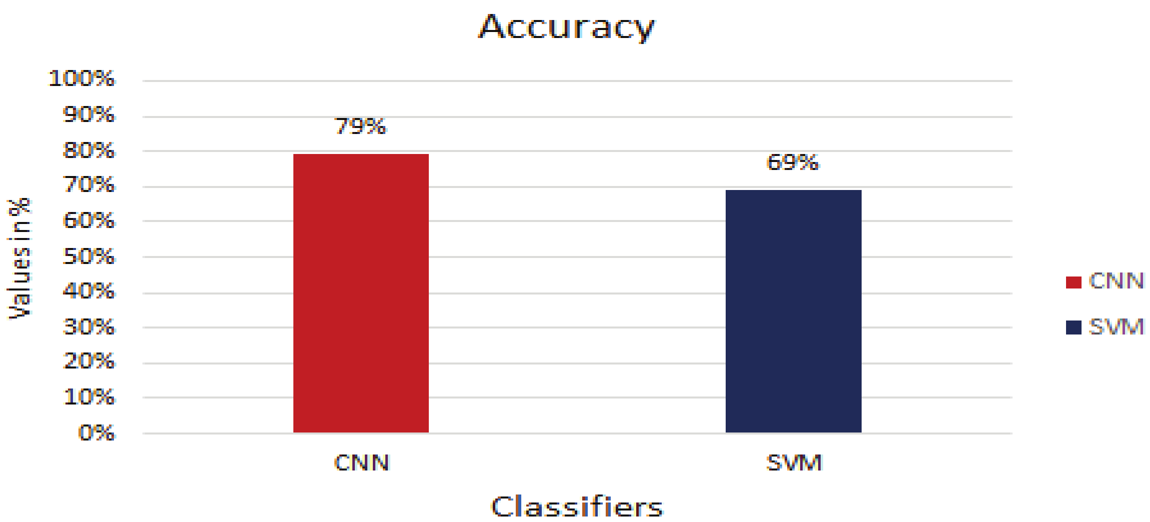

Fig. 4.2. Accuracy comparison of CNN and SVM classifiers for stress prediction.

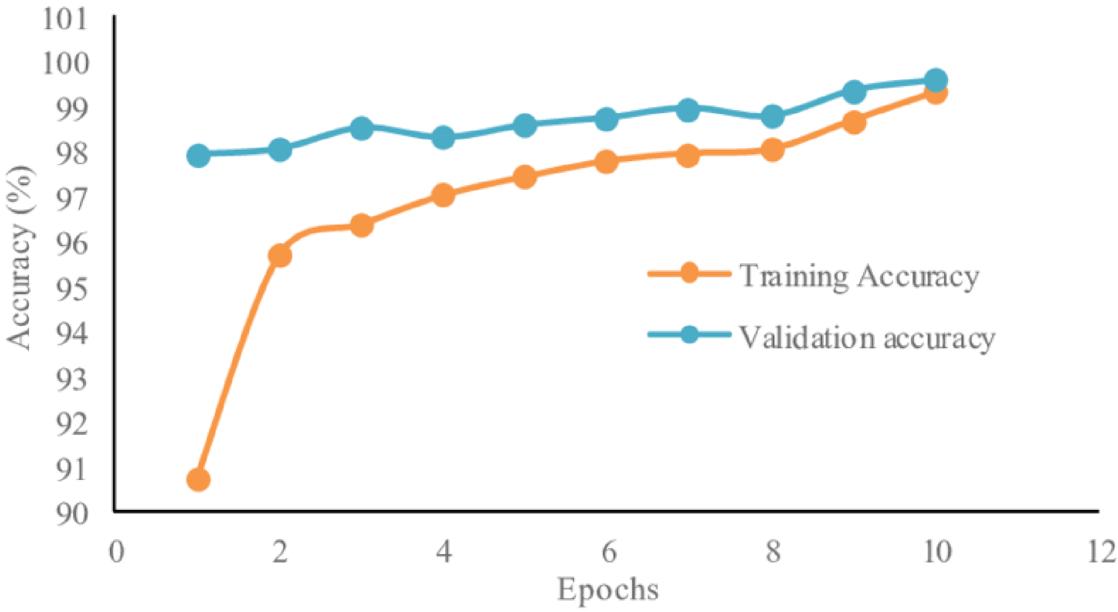

Fig. 4.3. Training and validation accuracy of the CNN model over different epochs.

V. COMPARISON TO TRADITIONAL METHODS

Traditional stress assessment approaches rely on self-reported questionnaires, interviews, and periodic psychological evaluations to identify an individual's mental state. While these methods provide basic insights into stress conditions, they often suffer from subjectivity, delayed feedback, and limited scalability. Moreover, they are not suitable for continuous monitoring in dynamic working environments. In contrast, the proposed machine learning–based stress identification framework integrates automated data analysis and intelligent classification techniques, offering significant improvements across multiple dimensions.

Improved Prediction Accuracy

Conventional stress assessment methods depend heavily on human perception and self-reporting, which may not always reflect actual stress levels. Additionally, these approaches are unable to capture complex relationships among physiological and behavioural factors. The proposed system employs supervised machine learning algorithms and deep learning models to learn patterns directly from numerical and facial image data. By analysing features such as working hours, sleep duration, heart rate, and facial expressions, the system accurately identifies stress levels. This data-driven approach enhances classification accuracy and enables reliable detection of varying stress conditions.

Real-Time and Continuous Monitoring

Traditional techniques are typically conducted at fixed intervals, making it difficult to identify sudden changes in stress levels. As a result, early warning signs may go unnoticed. The proposed framework supports continuous data acquisition and automated analysis, enabling real-time stress monitoring. This allows early detection of rising stress levels and facilitates timely intervention.

Reduced Human Dependency

Manual assessment methods require expert involvement and individual participation, which increases operational cost and time. The proposed system minimises human dependency by automating the stress identification process using machine learning models. Once trained, the system can independently analyse incoming data and generate predictions without manual supervision.

Efficient Resource Utilisation

Traditional stress evaluation methods require repeated surveys, expert analysis, and manual interpretation, leading to higher resource consumption. The proposed framework processes data automatically and filters relevant features, reducing computational and human resource overhead. This makes the system efficient and scalable for large organisational environments.

Enhanced Workplace Decision Support

The proposed system provides quantitative outputs such as predicted stress levels and performance metrics, which can be used by organisations to design wellness programs and preventive strategies. This supports data-driven decision-making for improving employee well-being and productivity.

VI. CONCLUSION

This paper presented a machine learning–based stress identification system for working environments that aims to provide an automated, reliable, and efficient solution for detecting stress levels among employees. The proposed framework utilises physiological and behavioural parameters such as working hours, sleep duration, and heart rate, along with facial expression features extracted using image processing techniques. Multiple machine learning algorithms and a deep learning CNN model were implemented and evaluated to analyse their effectiveness in stress classification.

Experimental results demonstrate that ensemble-based machine learning models, particularly Random Forest, outperform individual classifiers for numerical data. Furthermore, the integration of CNN-based facial expression analysis significantly enhances prediction accuracy. The hybrid approach achieves superior performance compared to standalone models, confirming the effectiveness of combining multimodal features for stress detection.

The proposed system offers several advantages, including real-time monitoring capability, reduced human dependency, and improved prediction accuracy. By enabling early identification of stress, the system can assist organisations in implementing timely interventions and preventive strategies to improve employee well-being and workplace productivity. Overall, the proposed framework provides a scalable and cost-effective solution for intelligent stress monitoring in modern working environments.

VII.REFERENCES

[1] S. Cohen, T. Kamarck, and R. Mermelstein, "A global measure of perceived stress," *Journal of Health and Social Behavior*, vol. 24, no. 4, pp. 385–396, 1983.

[2] R. S. Lazarus and S. Folkman, *Stress, Appraisal, and Coping*. New York, NY, USA: Springer, 1984.

[3] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *Journal of Computer and System Sciences*, vol. 55, no. 1, pp. 119–139, 1997.

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

[5] Z. Zhang, M. Lyons, M. Schuster, and S. Akamatsu, "Comparison between geometry-based and Gabor-wavelets-based facial expression recognition using multi-layer perceptron," *Proceedings of the IEEE International Conference on Automatic Face and Gesture Recognition*, pp. 454–459, 1998.

[6] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 511–518, 2001.

[7] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[8] J. Friedman, "Greedy function approximation: A gradient boosting machine," *Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, 2001.

[9] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, no. 2, pp. 156–166, 2005.

[10] G. Castellano, L. Kessous, and G. Caridakis, "Emotion recognition through multiple modalities: Face, body gesture, speech," *Affective Computing and Intelligent Interaction*, pp. 92–103, 2007.

[11] W. Burns and K. F. Knapp, "Stress measurement: A review of physiological measures," *Journal of Occupational Health Psychology*, vol. 12, no. 2, pp. 87–102, 2007.

[12] M. Z. Poh, N. C. Swenson, and R. W. Picard, "A wearable sensor for unobtrusive, long-term assessment of electrodermal activity," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 5, pp. 1243–1252, 2010.

[13] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[14] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Advances in Neural Information Processing Systems*, pp. 1097–1105, 2012.

[15] A. Sano and R. W. Picard, "Stress recognition using wearable sensors and mobile phones," *Proceedings of the International Conference on Affective Computing and Intelligent Interaction*, pp. 671–676, 2013.

[16] F. Ringeval et al., "AVEC 2013: The continuous audio/visual emotion and depression recognition challenge," *Proceedings of the ACM International Conference on Multimedia*, pp. 3–10, 2013.

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

[18] A. Gjoreski et al., "Continuous stress detection using a wrist device: In laboratory and real life," *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 1185–1193, 2016.

[19] A. Can, S. Arnrich, and C. Ersoy, "Stress detection in daily life scenarios using smart phones," *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 3, pp. 1–9, 2016.

[20] M. Abadi et al., "TensorFlow: A system for large-scale machine learning," *Proceedings of the USENIX Symposium on Operating Systems Design and Implementation*, pp. 265–283, 2016.

[21] T. Baltrušaitis, P. Robinson, and L.-P. Morency, "OpenFace: An open source facial behavior analysis toolkit," *Proceedings of the IEEE Winter Conference on Applications of Computer Vision*, pp. 1–10, 2016.

[22] H. Wang, Y. Li, and X. Hu, "Emotion recognition using deep learning: A survey," *IEEE Access*, vol. 7, pp. 117029–117043, 2019.

[23] M. Gjoreski et al., "Machine learning and end-to-end deep learning for continuous stress detection from wrist data," *IEEE Access*, vol. 8, pp. 1–12, 2020.

[24] S. Li and W. Deng, "Deep facial expression recognition: A survey," *IEEE Transactions on Affective Computing*, vol. 13, no. 3, pp. 1195–1215, 2022.

[25] J. Kim, H. Lee, and S. Park, "Multimodal stress detection using physiological signals and deep learning," *IEEE Access*, vol. 11, pp. 21456–21468, 2023.

[26] A. Kumar and R. Sharma, "Workplace stress detection using machine learning and wearable sensors," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 3, pp. 112–120, 2023.

[27] Y. Chen, X. Zhang, and L. Wang, "Facial expression based stress recognition using convolutional neural networks," *Proceedings of the IEEE International Conference on Artificial Intelligence and Signal Processing*, pp. 1–6, 2023.

[28] S. Patel and M. Verma, "An intelligent framework for employee stress monitoring using hybrid machine learning techniques," *IEEE Access*, vol. 12, pp. 44567–44578, 2024.

[29] R. Singh, P. Kaur, and A. Joshi, "Deep learning-based emotion and stress recognition in workplace environments," *IEEE Transactions on Affective Computing*, vol. 15, no. 2, pp. 356–368, 2024.

[30] L. Zhao and Q. Liu, "Multimodal stress analysis using physiological signals and facial images," *Proceedings of the IEEE International Conference on Computer Vision and Pattern Recognition Workshops*, pp. 221–229, 2024.

[31] K. Mehta and S. Nair, "Explainable artificial intelligence for stress detection using multimodal data," *IEEE Access*, vol. 13, pp. 10234–10248, 2025.

[32] T. Wang, Y. Huang, and J. Zhou, "Real-time workplace stress monitoring using deep learning and IoT," *IEEE Internet of Things Journal*, vol. 12, no. 1, pp. 455–467, 2025.