Journal of
Mobile Computing, Communications & Mobile Networks

ISSN: 2349-901X
Volume 12, Issue 1, 2025
January–April
DOI (Journal): 10.37591/JoMCCMN

https://journals.stmjournals.com/jomccmn

Review JoMCCMN

Employee Well-Being: Deep Learning Approaches to Stress Detection

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Abstract

Stress has become a major concern for employee health, productivity, and overall well-being in today's fast-paced work environment. It is a growing global issue, affecting both individual employees and the productivity of organizations. Work-related stress occurs when the demands of a job surpass an individual's ability to manage, whether because of long hours, overwhelming responsibilities, or other pressures. Factors such as conflicts with coworkers or supervisors, constant changes, and job insecurity (e.g., potential layoffs) also contribute to stress. According to the National Health and Safety Commission, work-related stress is a leading cause of prolonged absenteeism. This research work introduces a proposed AI-driven system designed to monitor and manage workplace stress levels for employees. By utilizing advanced machine learning algorithms, this system offers real-time stress evaluations and customized strategies for managing stress. The study proposes a framework to detect and analyze emotional stress and anxiety through video-recorded facial expressions. To systematically induce fluctuations in emotional states (neutral, relaxed, and stressed/anxious), an experimental protocol was developed with various external and internal stimuli. The analysis focused overtime on involuntary and semi-voluntary facial expressions to objectively measure emotional responses. Key features examined include eye movements, mouth activity, head motion, and questionnaire responses, with some measured via camera-based photoplethysmography. A feature selection process identified the most reliable indicators, followed by a classification model to differentiate between neutral, stressed/anxious, and relaxed states. Self-reported ranking transformations were also incorporated. Additionally, this AI system provides managers with insights into overall team stress levels, enabling informed decisions to improve the workplace environment. Core elements of the framework include continuous monitoring, personalized feedback, and adaptability to individual stress triggers and responses. The AI's learning capability ensures ongoing refinement, making its stress management strategies increasingly effective over time. By implementing this AI system, organizations can proactively address workplace stress, fostering employee well-being, enhancing productivity, and reducing absenteeism. This study discusses the framework's design, underlying AI algorithms, data privacy considerations, and the potential impact on organizational culture and employee health.

Keywords: Employee well-being, stress management, workplace stress, DL, facial expression recognition

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Received Date: December 20, 2024
Accepted Date: January 06, 2025
Published Date: January 24, 2025

Citation: Jigar Dave, Khushbu Juneja. Employee Well-Being: Deep Learning Approaches to Stress Detection. Journal of Mobile Computing, Communications & Mobile Networks. 2025; 12(1): 52–58p.

INTRODUCTION

Stress is more common and serious in today's world. If not handled well, it can cause health problems and affect emotions, thoughts, actions, and overall well-being. Identifying stress early helps people take steps to manage it and reduce its bad effects.

Traditionally, identifying stress has depended on psychological surveys or consultations with professionals. However, the subjective nature of self-reported responses in such surveys often leads to skewed results, particularly when individuals choose not to disclose their true psychological conditions. To overcome these challenges, methods to detect stress automatically have been developed. These methods use wearable devices like smartphones with built-in sensors or special sensors to check things like heart rate (HRV), ECG, skin response (GSR), blood pressure, and brain activity (EEG). Though these methods give accurate results, they need physical devices, making it hard to detect stress without direct contact [1].

With the rise of contact-free video cameras and better data collection and analysis methods, video-based stress detection has become a good option [2]. It has many advantages over wearable devices:

- *Convenience:* It works well in places like schools, hospitals, and jails, where wearing devices may not be possible or allowed.
- *Cost-effectiveness:* Facilitates long-term, large-scale observation at an affordable price.
- *Natural analysis:* Captures continuous footage to assess stress without intrusion, reducing external influences.

This study aims to use contact-free video cameras to detect stress [3]. Recent research shows that facial features and expressions give important clues to identify stress. Stress is often linked to changes in body signals like heart rate, blood pressure, and skin response (GSR), as well as changes in physical actions. Many methods focus on studying facial features like mouth movement, head motion, heart rate, blinking, eye gaze, pupil size, and eye movements [4]. Techniques like the Facial Action Coding System (FACS) are also used to find stress by studying specific facial movements, called Action Units (AUs), in images.

In contrast to these methods that depend on manual feature extraction, this study utilizes deep learning to automatically learn feature representations for stress detection [5]. Additionally, it combines action-based cues with facial analysis to improve accuracy. For example, subtle behavioral changes, like touching the ear when calm versus tugging at hair when anxious, offer supplementary insights [6]. By merging facial expressions with action signals, this approach presents a more comprehensive method for stress detection using video (Figure 1).

To solve these problems, we suggest a Two-Leveled Stress Detection Network (TSDNet). This network first studies face and action features separately and then combines them using a weighted method to detect stress [7].

Detecting stress within lengthy video sequences, where subtle differences are often hidden, is a significant challenge [8]. To overcome this, we created some advanced methods to improve the detection process, including:

- *Face-level multi-scale pooling attention:* Captures small details in facial expressions.
- *Action-level frame attention:* Focuses on identifying key movements in actions.
- *Stream-weighted integrator:* Combines local and global attention methods to improve overall performance.

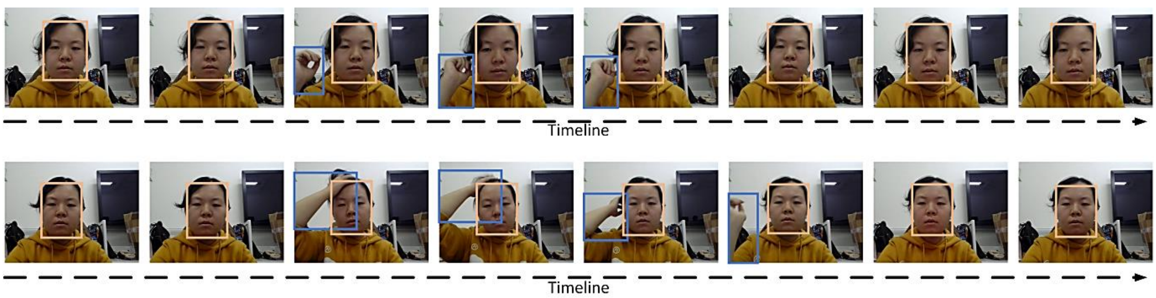

Figure 1. Two sets of images showing the same person watching a calm video clip (top) and a stressful video clip (bottom).

Key Contributions

- *Two-Level Stress Detection Network (TSDNet):* A new system that uses facial expressions and action movements from videos to detect stress effectively.
- *Improved attention techniques:* Special methods to extract emotional expressions and movements more accurately by combining detailed and overall views.
- *Dataset creation and testing:* We made a dataset of 2,092 labeled video clips. Testing showed that:
  TSDNet works better than older methods using manually designed features, achieving 85.42% accuracy and an F1-score of 85.28%. This shows that deep learning is effective for analyzing expressions and movements to detect stress. Integrating facial and action features improves performance, surpassing single-modality methods (face or action alone) by over 7% in both accuracy and F1-score.

LITERATURE REVIEW

Video-Based Stress Detection

Based on Facial use

Building on image-centric studies a framework was proposed that captured features related to eye movement, mouth activity, head gestures, and heart rate through facial videos. These indicators successfully identified stress and anxiety levels in participants [9]. In a similar vein, another study introduced a semi-automated algorithm for analyzing mouth movements by utilizing Eigen-features and template matching, achieving reliable classification on a sample of 25 individuals [10].

Based on Facial Action Units (AUs)

Recent research emphasizes the importance of physical behavior alongside facial expressions. Subtle actions such as head tilts or hand gestures can enhance facial indicators in stress detection. Studies have shown that gaze direction, saccadic movements, and blink frequency are significantly associated with stress levels [11].

Combining Visual and Thermal Spectra for Stress Detection

Key Advancements of This Work

This research advances the field by utilizing a deep learning approach, which removes the need for the time-consuming task of manual feature extraction. Additionally, it uniquely combines facial expression analysis with cues from user behaviors. We use a stream-weighted integration method, improved with local and global attention techniques, to increase the accuracy of stress detection compared to traditional methods.

OBJECTIVES/AIMS

The primary goal of this initiative is to develop an AI-driven system that monitors and manages stress levels among employees in real-time. This system aims to enhance employee well-being, boost productivity, and foster a healthier workplace environment. The approach involves continuous stress assessment, personalized interventions, and actionable insights for both employees and managers.

Key Objectives

1. *Real-Time Stress Monitoring:* Design a system to assess stress levels in real time by collecting: physiological data: heart rate variability, galvanic skin response, cortisol levels, etc. Environmental data: noise levels, lighting conditions, workload intensity, etc.
2. *Accurate Stress Detection and Analysis:* Employ advanced machine learning algorithms to process the collected data, accurately identifying stress patterns and predicting potential stress events. Develop models capable of identifying individual stressors and distinguishing between acute and chronic stress.
3. *Personalized Stress Management Interventions:* Create tailored intervention strategies based on individual stress profiles and preferences. Include suggestions such as breaks, task adjustments, mindfulness exercises, ergonomic changes, breathing techniques, and other stress-relief activities.

4. *User-Friendly Accessibility:* Develop an intuitive interface for employees to interact with the system, access stress reports, and receive intervention recommendations. Ensure compatibility across multiple platforms, including desktop, smartphones, and wearable devices, to encourage widespread and consistent use.
5. *Data Privacy and Security:* Implement robust measures to secure sensitive employee health information. Maintain transparency regarding data collection, storage, and usage practices, adhering to relevant data protection regulations.
6. *Organizational Insights for Managers:* Provide managers with aggregated, anonymized data to identify high-stress environments or periods. Enable informed decision-making to improve workplace conditions and support team well-being. Offer training and resources to managers for implementing effective stress management practices within their teams.
7. *Continuous Learning and System Improvement:* Incorporate machine learning capabilities to refine accuracy and efficiency based on ongoing data inputs and user feedback. Regularly update the system in response to user feedback, new research findings, and advancements in AI and stress management technologies.

RESEARCH METHOD/METHODOLOGY

Information Gathering

To identify stress, we utilize multimodal data, including:

- *Physiological Signals:* Wearable devices capture data such as skin temperature, electrodermal activity (EDA), and heart rate.
- *Behavioral Data:* Cameras record facial expressions, typing patterns, and speech characteristics (Figure 2).
- *Questionnaire Data:* Customized questionnaires collect insights into behavioral patterns, workload levels, work categories, and other relevant employee information.

The Perceived Stress Scale (PSS) is a well-established tool for assessing stress levels. Originally developed in 1983, it continues to be widely used to explore how various situations influence our feelings and perceived stress. This scale includes questions about your emotions and thoughts over the past month. For each question, you will indicate how often you experienced a specific feeling or thought. While some questions may seem similar, each one is distinct and should be treated individually. To get the most accurate results, respond quickly and intuitively: do not overanalyze or try to recall exact instances. Instead, select the option that feels like a reasonable estimate.

Choose an option from the list below for each question:
0: Not at all, 1: Hardly ever, 2: Sometimes, 3: Quite often, 4: Almost always

1. _______Over the once weeks, how frequently have you felt worried due to commodity unanticipated?
2. _______ Over the past weeks, how often have you felt unable to handle important things in your life?
3. ________Over the past weeks, how often have you felt nervous or stressed?
4. ________Over the past weeks, how often have you felt confident in your ability to deal with personal problems?
5. ________Over the past weeks, how often have you felt that things were going your way?
6. ________Over the past weeks, how often have you felt unable to manage everything you needed to do?
7. ________Over the past weeks, how often have you been able to handle the annoyances in your life?
8. ________Over the past weeks, how often have you felt in control and on top of things?
9. ________Over the past weeks, how often have you felt frustrated by things beyond your control?
10. ________Over the past weeks, how often have you felt overwhelmed by problems piling up?

Calculating Your PSS Score

Follow these steps to compute your Perceived Stress Scale (PSS) score:

- Reverse Scoring for Specific Questions, for questions 4, 5, 7, and 8, reverse your responses using the following scale: 0 becomes 4, 1 becomes 3, 2 remains 2, 3 becomes 1, 4 becomes 0. Summing the Scores, your ultimate PSS score is calculated by adding the points for each item.
- *Interpreting Your Score:* Scores range from 0 to 40, Low stress: 0–13, Moderate stress: 14–26, High stress: 27–40. Your perception of life events is central to the PSS, making it a meaningful tool. Even if two individuals experience identical situations, their stress levels may differ based on their perceptions.

Model Design

The model's performance is evaluated using the following approach:

- *Recurrent Neural Networks (RNNs):* These are used to study sequential data and identify patterns over time.
- *Convolutional Neural Networks (CNNs):* Extract features from visual and physiological inputs.

The model is trained on datasets like WESAD (Wearable Stress and Affect Detection) and fine-tuned for workplace-specific stress scenarios to improve its accuracy and applicability.

Evaluation Metrics

The following standards are used to assess the model's performance:

- *Effectiveness in Stress Detection:* Accuracy, Precision, Recall, F1 Score, Operational Efficiency: Low latency, and Real-time applicability in workplace environments.

RESULT/FINDINGS

The deep convolutional neural network showed excellent results, with 99.80% accuracy for binary classification and 99.55% accuracy for 3-class classification. The deep multilayer perceptron neural network also performed strongly, achieving 98.38% accuracy for 3-class classification and 99.65% accuracy for binary classification. These results are a big improvement over earlier methods that used physiological signals for binary stress detection and 3-class emotion classification.

DISCUSSION/ANALYSIS

Comparison of Deep Neural Networks with Traditional Machine Learning Algorithms

Deep neural networks like the 1D convolutional neural network and multilayer perceptron performed better than traditional machine learning methods. For both binary stress detection and 3-class emotion classification, these networks achieved higher accuracy and F1 scores.

This improvement was consistent whether all physiological signals, including 3-axis ACC sensor data, were used or not. The results clearly show the advantage of deep neural networks over traditional methods in multiple aspects.

Higher Accuracy

The deep neural networks were 6–12% more accurate for binary stress detection and 17–23% more accurate for 3-class emotion classification compared to traditional methods. This improvement was consistent in scenarios with and without 3-axis ACC sensor data.

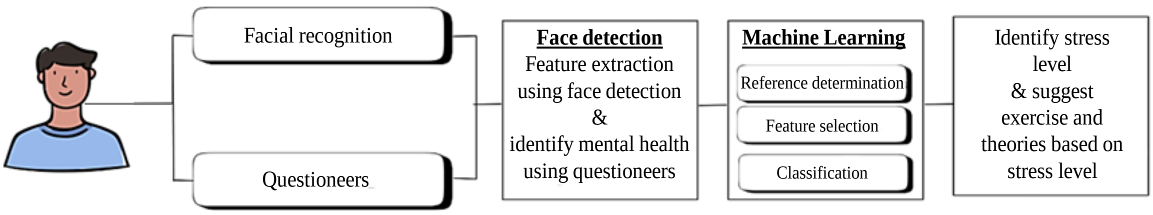

Figure 2. Facial expression recognition.

Simpler and Consistent Architecture

Deep neural networks used the same architecture for both tasks. For binary stress detection, the final layer had one unit with a sigmoid activation function, while for 3-class emotion classification, it had three units with a Softmax activation function. In contrast, traditional methods required different algorithms for different tasks. For example, Random Forest performed best without ACC sensor data, while AdaBoost performed better with ACC sensor data in emotion classification. This makes traditional methods harder to use in real-world applications as they need multiple models for different tasks. Deep neural networks provide a simpler and more practical solution.

Consistent Performance Across Tasks

Deep neural networks maintained high performance across both tasks, with only a small drop in accuracy (0.25 to 3.98%) when moving from binary stress detection to 3-class emotion classification. Traditional methods, however, showed a larger drop in accuracy (over 10%) for the same transition. This shows that deep neural networks are better at understanding and learning from physiological signals.

Better Use of ACC Sensor Data

Deep neural networks performed even better when data from the 3-axis ACC sensor was included. On the other hand, traditional methods often showed a performance drop (0.29 to 3.84%) when ACC sensor data was added. This shows that deep neural networks are better at using additional data effectively, making them more suitable for tasks involving ACC sensor signals. In summary, deep neural networks are more accurate, consistent, and practical for real-world applications compared to traditional machine learning algorithms.

CONCLUSION/SUMMARY

In this study, we explored the application of deep learning techniques for stress detection, focusing on enhancing employee well-being through more accurate and reliable detection methods. The results show that deep neural networks, particularly the deep 1D convolutional neural network and deep multilayer perceptron neural network, surpass traditional machine learning algorithms in both binary stress detection and multi-class emotion classification tasks. These models consistently achieved higher accuracy rates and F1 scores, showcasing their potential in real-world applications for monitoring employee stress and emotions.

Furthermore, the inclusion of physiological signals, especially from the 3-axis ACC sensor, significantly improved the performance of the deep learning models, providing valuable insights into the potential of using wearable technology for continuous monitoring of employee well-being. The deep neural networks' ability to learn complex patterns from the physiological signals and maintain consistent performance across different tasks highlights their robustness and suitability for stress detection applications.

However, there are limitations, especially regarding the training dataset, which was relatively small and might not fully capture the diversity of the broader population. Future research should aim to expand the dataset and include a broader range of participants to enhance the generalizability and robustness of the models. By addressing these limitations and refining the models, deep learning approaches have the potential to transform the way employee stress and well-being are monitored and managed, contributing to healthier work environments and improved overall productivity.

Limitations

For future research, it is important to train and test the two neural networks using much larger datasets that include people from different backgrounds. This will make the models stronger and more reliable by giving them a better understanding of the general population. In this study, the dataset had information from only 15 participants, which may not fully reflect the differences seen in a larger group of people. The idea of using a more diverse dataset comes from the fact that stress sensitivity and how people experience stress can be very different from person to person. A bigger and more varied dataset will help the models work better and give more accurate results for different groups of people.

Recommendations

- *Expand Datasets:* Use larger, diverse datasets to improve model robustness and ensure better representation of different employee demographics.
- *Incorporate Multi-Modal Data:* Integrate data from various sensors (e.g., heart rate, skin conductance, EEG) to enhance stress detection accuracy.
- *Real-Time Monitoring:* Implement real-time stress monitoring systems to provide timely interventions and support.
- *Personalized Models:* Develop individualized stress detection models to tailor interventions for each employee.
- *Ensure Privacy and Ethics:* Prioritize employee privacy and adhere to ethical standards when handling physiological data.
- *Integrate Mental Health Support:* Use stress detection insights to complement workplace mental health programs and resources.
- *Test in Workplaces:* Evaluate models in real-world settings to refine their usability and effectiveness.
- *Continuous Improvement:* Regularly update models to adapt to evolving workplace stressors and enhance accuracy.

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