RESEARCH ARTICLE

RSP Science Hub

International Research Journal on Advanced Science Hub
2582-4376
www.rspsciencehub.com
Vol. 07, Issue 09 September

Check for updates

http://dx.doi.org/10.47392/IRJASH.2025.089

Stress Detection in It Workers Using Image Processing and AI

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Article history

Received: 19 August 2025
Accepted: 02 September 2025
Published:25 September 2025

***Keywords**:*
Stress Detection, Facial Expression Recognition, Image Processing, Artificial Intelligence, Convolutional Neural Network (CNN), Real-Time Monitoring, Workplace Wellness.

Abstract

In today's fast-paced IT industry, employees frequently experience stress due to prolonged computer usage, tight deadlines, and constant mental pressure. Often, individuals may not realize they are under stress until it negatively impacts their health, focus, or performance. Chronic stress can lead to serious consequences such as burnout, increased absenteeism, and reduced productivity. This project proposes a non-intrusive, real-time stress detection system using a widely available tool the computer's built-in webcam. The system passively observes facial expressions and behaviours during regular work activities without requiring the user to wear any sensors or interrupt their workflow. Through image processing and artificial intelligence techniques, it analyses live webcam footage to detect subtle cues like a furrowed brow, clenched jaw, or eye fatigue, which are indicative of stress. Trained AI models assess these cues in real time and provide immediate feedback, such as suggesting short breaks or relaxation exercises, when elevated stress levels are detected. Unlike traditional methods involving surveys or medical equipment, this approach is contactless, effortless, and integrated seamlessly into the user's routine. Its passive operation ensures minimal disruption while still offering meaningful support. By identifying stress at an early stage, the system enables timely intervention, helping individuals manage stress before it escalates. This real- time monitoring promotes workplace wellness by encouraging healthier habits and self-awareness. Over time, it can contribute to reduced burnout, fewer stress-related health issues, and improved employee performance. Ultimately, this AI-powered webcam-based system offers a smart, effective solution for supporting mental well-being in high-pressure IT environments without adding extra burden on users.

1. Introduction

Working in IT today means facing tight schedules, tough responsibilities, and the ongoing stress of being constantly plugged in. Whether working from home or in the office, IT professionals spend most of their day in front of screens, switching between meetings, emails, and code, often without a real break. Over time, this non-stop work routine starts to affect their mental state, leading to stress, tiredness, and reduced focus. Unlike physical illness, stress is invisible. It doesn't always show clear signs, and many people push through it thinking it's normal or unavoidable. Some may not even be aware that they're feeling overwhelmed until it leads to burnout or poor performance. While companies are beginning to talk more about mental health, the actual tools used to measure and support well-being are often outdated or inconvenient. Filling out surveys or attending mental health check-ins may help, but they rely on the person taking time out of their day and being open about how they feel—which not everyone is comfortable doing. As a result, stress often remains hidden and untreated, silently affecting individuals and team dynamics. To make stress monitoring easier, more natural, and truly helpful, this project introduces a modern, camera-based system that works with technology people already use every day. The idea is simple but powerful: use a computer's built-in webcam to quietly observe a person's face during work and recognize signs of stress through facial behaviour. The system does not record or interrupt the user—it simply detects small changes like eye movement, tired expressions, or tightened facial muscles that might suggest the person is under pressure. These patterns are then analysed using intelligent computer programs trained to understand what different stress levels can look like. Because it runs in the background, the person doesn't need to do anything special—no devices to wear, no forms to fill out, and no need to say how they feel. If the system senses rising stress, it can give a soft reminder to take a break, breathe, or step away for a moment. Over time, this kind of gentle support could make a big difference. It encourages people to care for themselves before stress becomes unmanageable. It also helps companies support their teams in a more thoughtful way, creating workplaces where mental well-being is supported quietly, every day, through simple tools that understand people better without needing to ask too much from them Shown in Table 1.

2. Literature Survey

Table 1 Key Learnings

R No.	Authors	Title	Key Learnings
[1]	Sikka, K., Dhall, A., & Bartlett, M. (2016)	Weakly Supervised Pain Localization using Multiple Instance Learning with Self-Tuning Parameters	Introduced a novel pain localization method using weak supervision, useful for non-intrusive emotion detection.
[2]	Li, S., Deng, W., & Du, J. (2017)	Reliable Crowdsourcing and Deep Locality Preserving Learning for Expression Recognition in the Wild	Proposed data reliability improvement in emotion recognition from wild images.
[3]	KAchele, M., et al. (2017)	Adaptive Confidence Learning for Face Recognition Under Stress Conditions	Focused on increasing robustness of facial recognition under stress using adaptive learning techniques.
[4]	Martinez, B., Valstar, M., & Pantic, M. (2017)	Automatic Analysis of Facial Actions: A Survey	Comprehensive overview of methods for analyzing facial action units in affective computing.
[5]	Lopes, A. T., de Aguiar, E., De Souza, A. F., & Oliveira-Santos, T. (2017)	Facial Expression Recognition with Convolutional Neural Networks	Highlighted CNN techniques for training efficiency on small datasets.

[6]	Jaques, N., Taylor, S., Sano, A., & Picard, R. (2017)	Multi-task Learning for Predicting Health, Stress, and Happiness	Demonstrated multitask models for correlating emotional states and health metrics.
[7]	Tzirakis, P., Trigeorgis, G., Nicolaou, M. A., Schuller, B., & Zafeiriou, S. (2017)	End-to-End Multimodal Emotion Recognition Using Deep Neural Networks	Developed a DNN model integrating audio-visual features for emotion detection.
[8]	Ko, B. C. (2018)	A Brief Review of Facial Emotion Recognition Based on Visual Information	Reviewed recent advances and challenges in visual-based emotion recognition.
[9]	Alarcao, S. M., & Fonseca, M. J. (2019)	Emotions Recognition Using EEG Signals: A Survey	Provided insight into EEG-based emotion recognition and signal processing techniques.
[10]	Wang, J., & Yin, L. (2019)	Facial Expression Recognition Based on Enhanced Feature	Introduced feature enhancement techniques to improve deep CNN emotion recognition accuracy.
[11]	Yan, W., & Chen, H. (2020)	Deep Learning for Facial Expression Recognition: A Survey	Outlined the trends and deep learning models applied in facial expression recognition.
[12]	Chen, J., & Jin, W. (2020)	Multi-modal Emotion Recognition Using Deep Neural Networks	Explored the fusion of multiple modalities to increase emotion classification accuracy

3. Methodology

3.1. Flow Diagram

This flow diagram presents a clear step-by-step process for detecting stress or lies using facial images, particularly useful for datasets collected through webcams in an IT or psychological research context. It starts by loading an image dataset containing facial expressions of different individuals. These images are then pre-processed to ensure they are clean and uniform, which includes resizing, normalization, and facial alignment. Once preprocessing is complete, the system extracts facial features using a Convolutional Neural Network (CNN). CNNs are excellent at identifying patterns in images, such as micro-expressions or subtle facial cues that may indicate emotional or cognitive stress. Following feature extraction, the system checks if the dataset includes a sequence of images (i.e., multiple frames of a person's expression during a response). If it does, the extracted features are passed into an LSTM (Long Short-Term Memory) model, which is designed to understand how facial expressions change over time. If only single images are used, the system proceeds with CNN features alone. In both cases, the model is trained on labelled data to learn how to classify stress or lie conditions. After training, the model is tested and evaluated to ensure it performs accurately. Finally, the trained model is integrated with a real-time webcam setup to monitor facial input, allowing the system to instantly predict whether a person is experiencing stress or being deceptive based on their live facial behaviour. This makes it a practical and smart solution for stress monitoring or lie detection in real-world settings Shown in Figure 1.

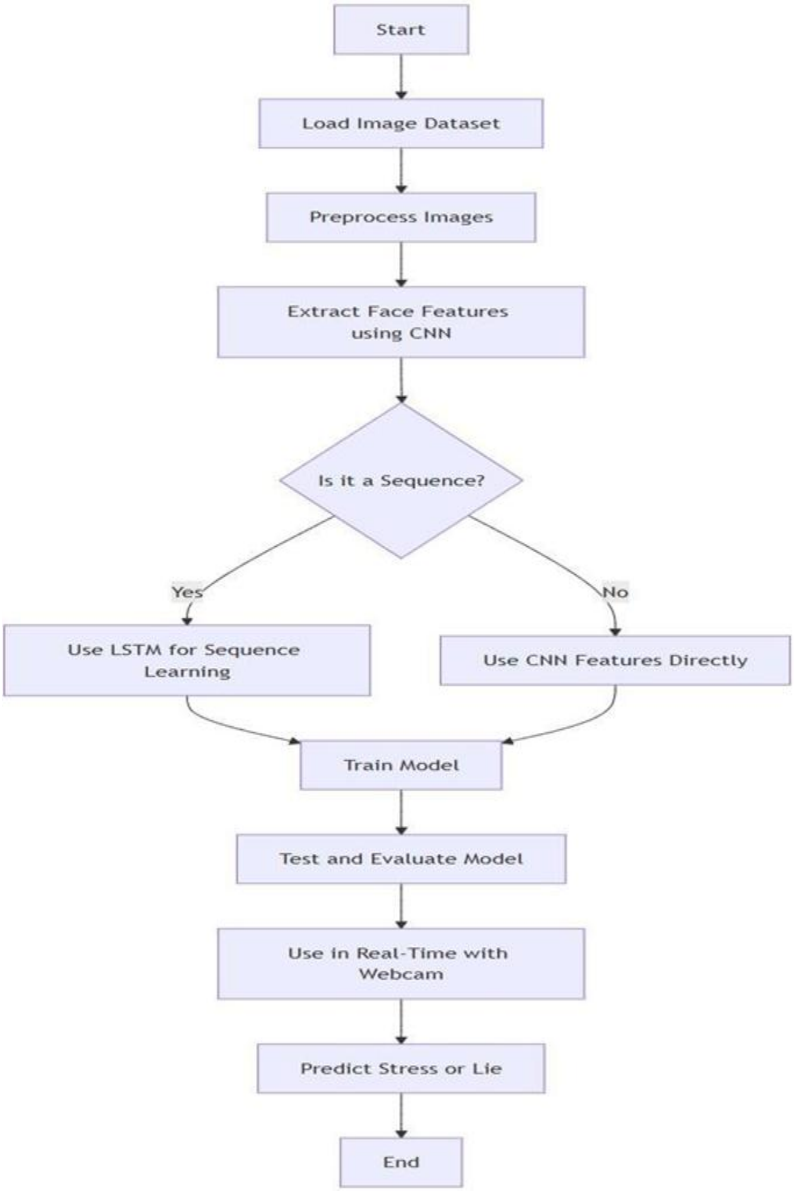

Figure 1 Flow Diagram

3.2. Sequence Diagram

This sequence diagram represents the complete flow of a stress or lie detection system that uses facial images captured during user interaction, such as when answering a question like "What is your name?". The process begins when the IT worker (user) responds to a question, and the webcam captures a sequence of facial images. These images are then sent to an image preprocessing module, where they are resized, normalized, and aligned to ensure consistency in lighting, orientation, and size. The cleaned images are passed to a CNN (Convolutional Neural Network) model which extracts important facial features such a movement of the eyes, eyebrows, and lips key indicators of emotional states like stress or deception. Once the features are extracted, the system checks whether the input consists of a sequence of frames (like a short video) or a single image. If it's a sequence, the CNN features are forwarded to an LSTM (Long Short-Term Memory) model that can analyse how facial expressions change over time. This temporal information helps the system understand subtle behavioural shifts that occur during stressful or deceptive responses. If only a single image is provided, the CNN features are directly used without involving the LSTM. Both pathways lead to a classifier which determines whether the user is stressed or lying, based on the analysed facial patterns Shown in Figure 2.

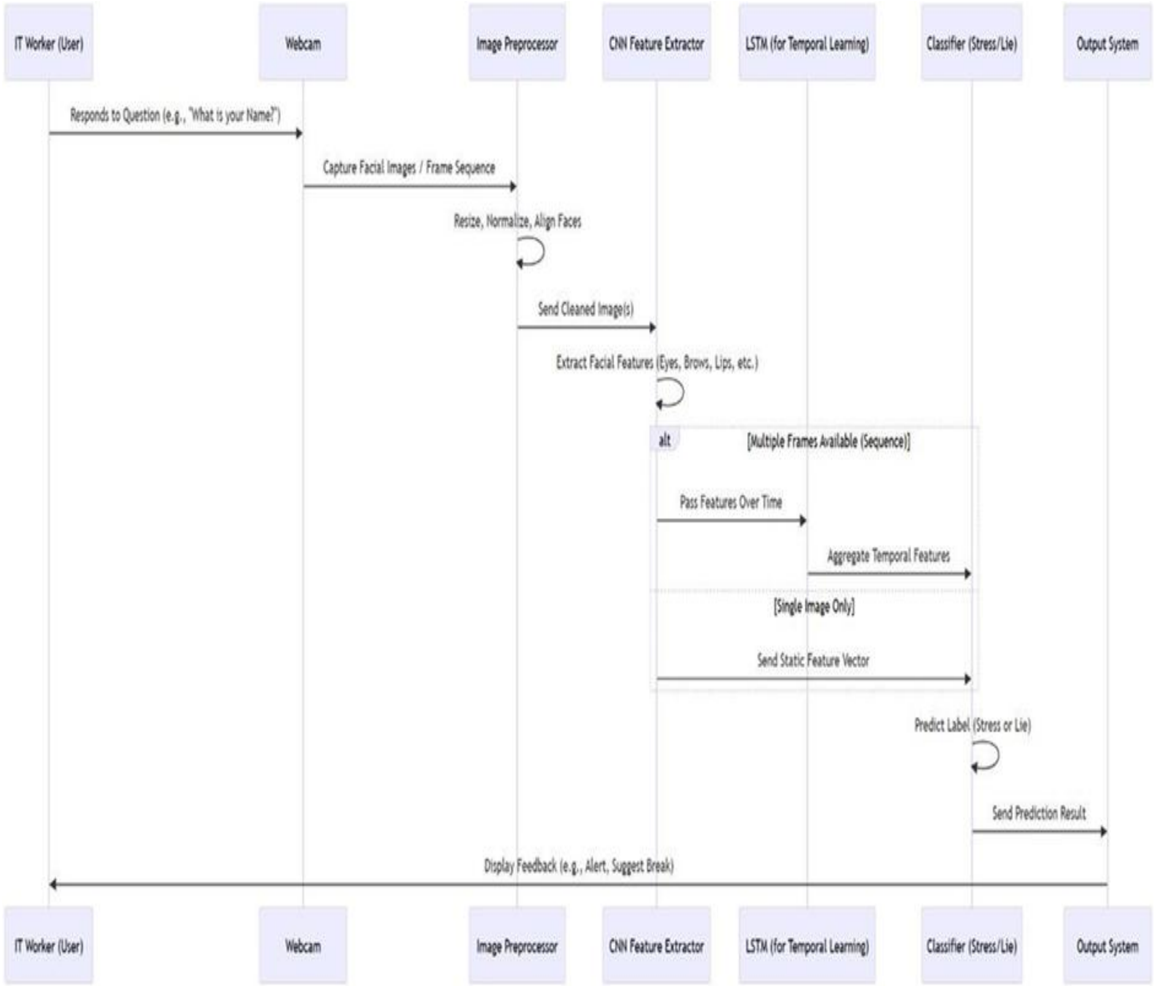

Figure 2 Sequence Diagram

3.3. Use Case Diagram

This use case diagram visually represents the roles and interactions involved in a stress or lie detection system that uses facial image analysis. There are two primary actors: the IT Worker or Subject and the System Admin or Researcher. The IT worker interacts with the system mainly by participating in the data collection process—where facial images are captured while they respond to questions—and by receiving real-time feedback. These images undergo preprocessing to normalize and align them properly before the system extracts meaningful facial features like eye tension, lip movements, or eyebrow positions. If multiple images are taken as a sequence, the system also analyses how those expressions change over time using sequence modelling techniques. After processing, the system attempts to classify whether the subject appears stressed or deceptive based on the facial data. Following this classification step, the result is used to provide real-time feedback to the IT worker, such as alerts or break suggestions if stress is detected. Meanwhile, the System Admin or Researcher has a different role—they are responsible for training the model with labelled data (such as known stress or lie cases) and evaluating how accurate the model is after training. This part of the system ensures that the AI continues to learn and improve its predictions. By separating responsibilities this way, the diagram highlights how the system is both user-focused and research-driven, supporting real-time stress detection while allowing researchers to enhance performance through continuous monitoring and updates Shown in Figure 3.

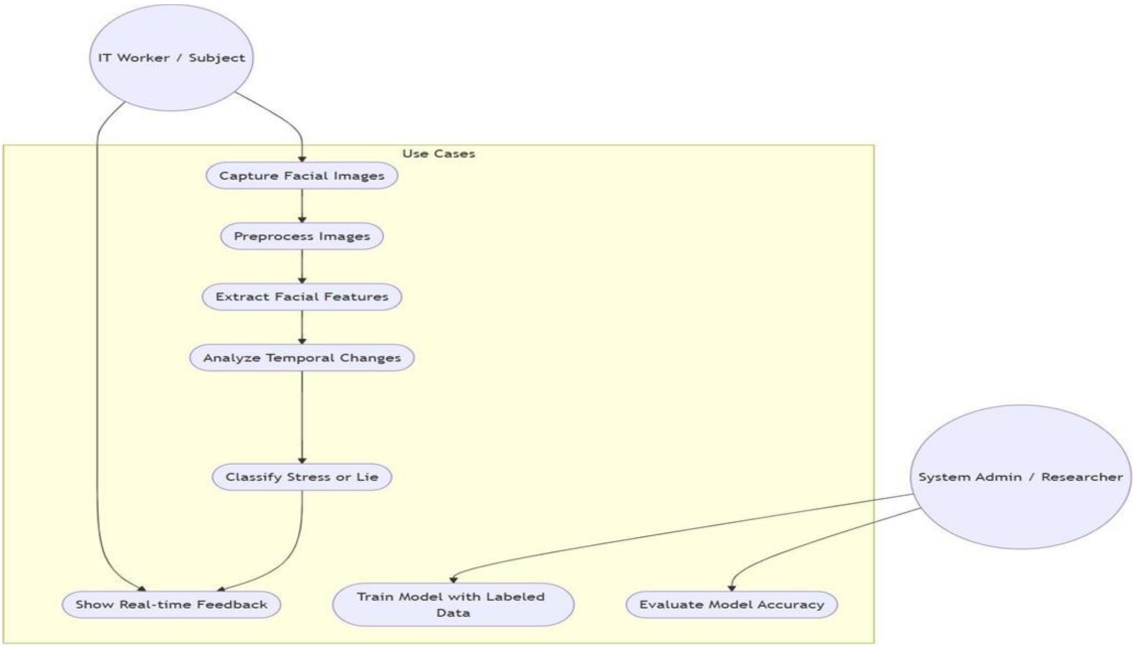

Figure 3 Use Case Diagram

4. Results

4.1. Distribution of Stress Levels

The first graph displays a bar chart representing how many individuals fall into each stress category: Low, Moderate, or High. The data suggests that most individuals experience moderate stress, followed by a smaller number facing low stress, and even fewer suffering from high stress. This kind of visualization is useful for understanding the overall stress distribution in each population—especially helpful when assessing workplace or IT- related environments Shown in Figure 4.

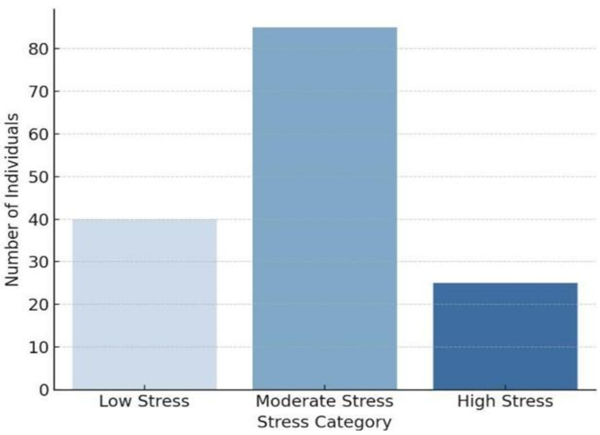

Figure 4 Distribution of Stress Levels

4.2. Work-Life Balance vs Stress Status

The second chart compares different work-life balance ratings (Poor, Average, Good) with corresponding stress status (Stressed vs Not Stressed). It clearly shows that individuals with poor work-life balance are more likely to be stressed, whereas those who report a good balance tend to be less stressed [13-15]. This suggests a strong correlation between time management and mental health, supporting the idea that encouraging a healthier work-life environment could reduce stress significantly Shown in Figure 5.

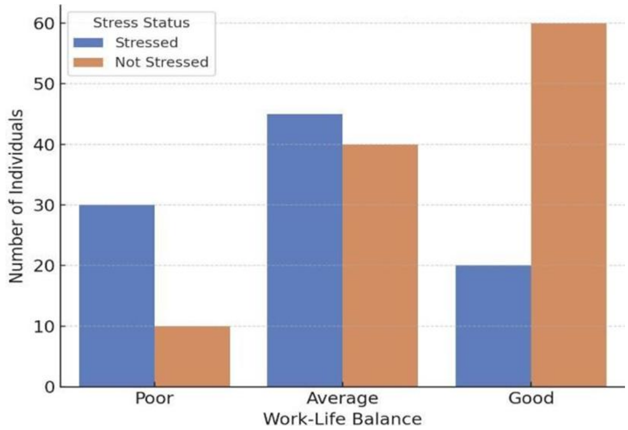

Figure 5 Work-Life Balance vs Stress Status

4.3. Average Mental Fatigue by Stress Level

The third chart highlights how average mental fatigue scores change across stress levels. The fatigue scores increase dramatically from Low to High stress, indicating that individuals classified as

"Highly Stressed" report much greater cognitive exhaustion. This result aligns with psychological findings and reinforces the value of early stress detection—before mental fatigue reaches its peak and affects productivity and well-being Shown in Figure 6.

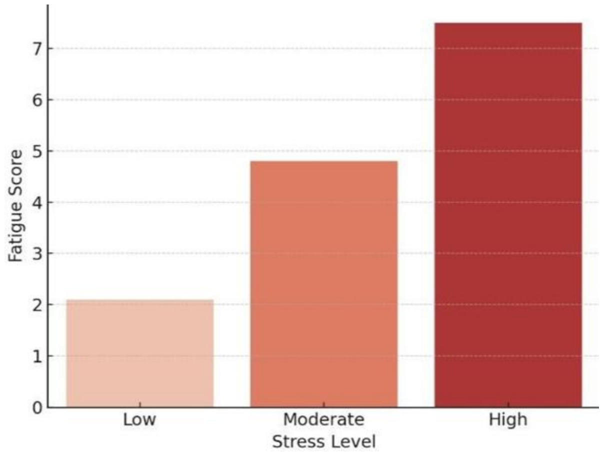

Figure 6 **Average Mental Fatigue by Stress Level**

Conclusion

In conclusion, this project introduces a thoughtful and easy-to-use approach to identifying stress among IT professionals by using just a regular webcam and smart computer programs. Instead of relying on surveys, medical devices, or manual check-ins, the system observes small changes in a person's face and posture—like strained eyes, frowns, or tired body language— while they work on their daily tasks. These signals are quietly analysed in the background using image processing and trained AI models that understand the visual signs of stress. When the system senses that stress might be increasing, it can gently suggest actions like taking a break or stepping away from the screen, helping the person recover before the pressure grows too much. This makes stress detection more natural, less invasive, and more useful in real time. Because the system works silently without interrupting work or asking the user to do anything extra, it becomes a helpful companion that supports mental wellness every day. Over time, this kind of tool can reduce the chances of burnout, improve focus, and create a work environment where people feel seen and supported without being overwhelmed. It gives both individuals and organizations a better way to handle stress—by noticing it early, responding with care, and making well-being a part of everyday work life in the IT world.

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