IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⸎ Peer-reviewed & Refereed journal ⸎ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14639

# STRESS DETECTION IN IT PROFESSIONAL BY IMAGE PROCESSING AND MACHINE LEARNING

**Prof. M. S. Sawalkar [1], Shubham Shende[2], Divyesh Kachave[3], Pratik Gole[4], Anuj Sinkar [5]**

Department of Computer Engineering, JSPM Narhe Technical Campus, Pune, Maharashtra, India[1]

BE Student, Department of Computer Engineering, JSPM Narhe Technical Campus, Pune, India[2-5]

**Abstract:** This research proposes a comprehensive system designed to detect stress levels among IT professionals by leveraging real-time facial analysis powered by advanced machine learning techniques. The underlying concept is based on the psychological understanding that human emotions are visually expressed through subtle facial movements and micro-expressions, making them valuable indicators for assessing an individual's mental and emotional state. By utilizing these non-intrusive cues, the system offers a privacy-conscious and continuous approach to psychological monitoring without requiring active user participation. At the core of the system is the use of Convolutional Neural Networks (CNNs), which are highly effective in processing and interpreting visual data, particularly for emotion recognition tasks. The Deep Face library is employed to extract deep feature representations from facial images, enabling accurate classification of emotions that correlate with varying levels of psychological stress. For initial face detection and localization, classical Haar Cascade classifiers are integrated, providing reliable identification of facial regions within both static images and live video streams. The implementation includes a web-based interface developed using the Django framework, which allows users to interact with the system in real time. This interface supports continuous webcam input, emotion-based feedback display, and optional logging of stress assessments, ensuring a user-friendly experience suitable for deployment in organizational settings. Experimental evaluations were conducted using both publicly available emotion datasets and live webcam feeds to validate the system's effectiveness. The results indicate high accuracy and consistent performance in classifying emotional states and estimating corresponding stress levels. These findings underscore the system's potential as a practical tool for real-time mental health monitoring in professional environments, particularly within the high-pressure context of the IT industry.

**Keywords:** Stress Identification, Facial Emotion Analysis, Machine Learning, Deep Face, CNN, Real Time Monitoring, IT Workforce.

## I. INTRODUCTION

Occupational stress is becoming an increasingly prevalent concern within the information technology (IT) sector. This can be attributed to a combination of factors, including prolonged working hours, constant exposure to mentally demanding tasks, tight deadlines, and frequent multitasking. Such conditions often contribute to elevated stress levels among professionals, which, if left unaddressed, may lead to burnout, decreased productivity, and even long-term health complications. While organizations have traditionally relied on subjective methods such as self-reported questionnaires, periodic surveys, or in-person psychological assessments to evaluate employee stress, these approaches are limited in scope. They often fail to capture real-time changes and are exposed to personal bias.

To overcome these limitations, recent advances in artificial intelligence and computer vision have paved the way for more objective, non-intrusive stress assessment techniques. One promising avenue is the analysis of facial expressions, which are closely tied to emotional and psychological states. Unlike traditional methods, facial emotion recognition enables continuous monitoring without interrupting the individual's workflow. In particular, deep learning models—especially Convolutional Neural Networks (CNNs)—have demonstrated high accuracy in identifying complex emotional cues from facial data.

This research presents a real-time stress detection system that utilizes a webcam to capture facial images, processes the input through the Deep Face framework for emotion-based feature extraction, and then interprets the data to estimate stress levels. The predicted emotional states are mapped to corresponding stress intensities using established psychological correlations. The system is integrated with a Django-based web application that offers immediate feedback to the user while ensuring that privacy is maintained throughout the process. This end-to-end solution aims to support mental health initiatives within corporate environments by providing a scalable, automated, and user-friendly tool for stress monitoring, thus addressing a critical need in the modern workplace.

DOI: 10.17148/IJARCCE.2025.14639

## II. LITERATURE REVIEW

Numerous studies have explored emotional and mental state detection using AI and vision-based systems:

- Alghowinem et al. (2016) employed multimodal features like eye tracking and head posture with SVM to detect signs of depression.
- Ma et al. (2016) introduced DepAudioNet, integrating CNN and LSTM for classifying depressive states using voice data.
- Zhu et al. (2017) proposed a two-stream deep learning model analyzing facial expressions and movements for automated depression diagnosis.
- Jan et al. (2017) combined vocal and facial cues using MFCC and FDHH to assess depression levels.
- He et al. (2016) presented Residual Networks (ResNet), which improved CNN performance and is commonly used in facial analysis. These contributions highlight the effectiveness of deep learning in identifying psychological patterns, supporting the feasibility of our image-based stress recognition system.

## III. METHODOLOGY

### A. System Architecture

The proposed system is built upon a modular design framework that facilitates real-time detection of psychological stress through facial emotion recognition. The pipeline is systematically organized into the following key phases:

1. Real-Time Image Acquisition
The process begins with the continuous capture of facial images using a webcam. This component serves as the live data input to the system, allowing immediate analysis of user facial expressions as they appear.

2. Preprocessing and Face Localization
To isolate facial regions, the system utilizes either Haar Cascade classifiers or Multi-task Cascaded Convolutional Networks (MTCNN). Once detected, facial images are cropped, resized to a standard resolution, and normalized. This preprocessing ensures uniformity across all input samples and improves the accuracy of downstream processing.

3. Extraction of Emotional Features
Deep Face, an advanced facial analysis framework, is employed to extract relevant features from the preprocessed images. By leveraging pre-trained deep learning models such as VGG-Face, Dlib, or Facenet, DeepFace generates meaningful embeddings that represent the user's emotional expression.

4. Emotion Classification and Stress Level Inference
The extracted embeddings are classified into basic emotion categories using a Convolutional Neural Network (CNN) that has been trained on labeled facial expression datasets. Each emotion is associated with a corresponding stress intensity—classified as low, moderate, or high—based on existing behavioral and psychological studies linking emotional states with stress indicators.

5. Web Interface Integration
A front-end interface developed using the Django web framework allows seamless user interaction. The module facilitates real-time image capture through a webcam, presents immediate stress level outputs, and optionally records the results in a database for future reference or evaluation.

### B. Tools and Technologies Employed

To build the proposed system, a combination of widely used open-source technologies has been adopted, each playing a critical role in the pipeline:

OpenCV:
Utilized for image and video capture directly from the webcam, along with basic image processing tasks such as resizing and grayscale conversion.

Deep Face Library:
A Python library that summarize various pre-trained deep learning models for facial recognition and emotion analysis. It abstracts complex deep learning operations and offers high reliability in feature extraction.

Django Web Framework:
This Python-based web framework is used to design the web interface, handle client-server communication, manage sessions, and present results in a browser environment.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14639

SQLite Database:
A file-based relational database system used to store records of classified emotions, corresponding timestamps, and optional user inputs or session metadata.

**C. Performance Evaluation Metrics**
To rigorously evaluate the system's effectiveness in emotion classification and stress prediction, the following metrics were considered:

Classification Accuracy:
Classification accuracy is the percentage of correct predictions made by the model out of all predictions. It shows how well the system can detect the correct emotion or stress level from facial expressions.

Precision, Recall, and F1-Score:
These statistical measures offer a more detailed understanding of how well the classification model performs. Precision evaluates how many of the predicted positive cases were correct, recall assesses how many actual positive cases were identified, and the F1-score balances both metrics, especially under class imbalance scenarios.

Confusion Matrix:
The summary that visualizes the model's classification outcomes in a table form. It allows identification of frequent misclassifications, such as confusion between similar emotional states (e.g., sadness and neutrality), thus helping pinpoint areas for improvement in the classifier's performance

## IV. GUI IMPLEMENTATION

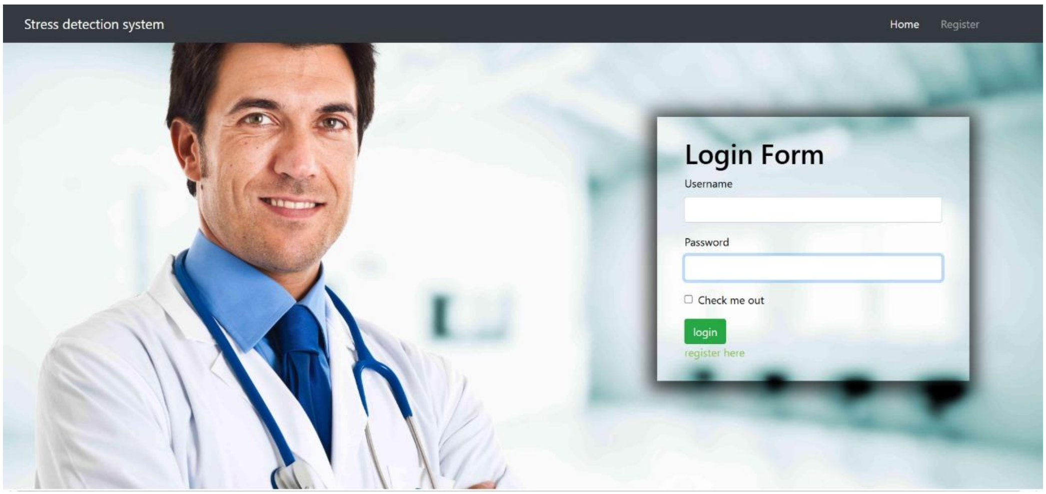




Fig 2: Registration form

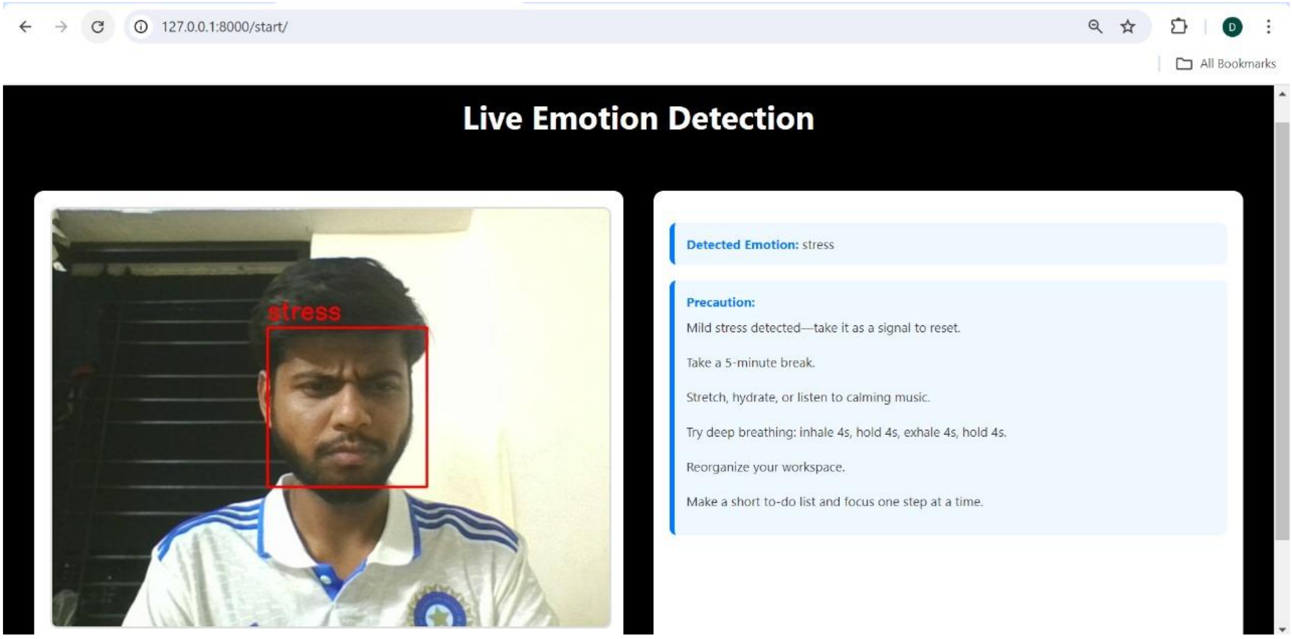
IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14639

## V. RESULTS




## VI. CONCLUSION

This study presents a real-time, non-intrusive stress detection system for IT professionals using facial expression analysis. By combining Haar Cascade for face detection, DeepFace for emotion recognition, and CNN for classification, the system effectively links emotions to stress levels. Integrated with a Django-based web interface, it enables instant feedback and practical usability in workplace settings. Test results from live webcam input and datasets confirm its accuracy and reliability. Moving forward, the system can be enhanced through broader datasets, refined stress mapping, and improved privacy measures to support ethical deployment.

## VII. FUTURE SCOPE

Using wearable devices to watch stress levels in real time and help quickly when needed.
Combining face analysis with other sensors to better find stress.
Creating personalized AI tools to help IT workers manage stress and stay healthy.
Applying this system to other stressful jobs and schools.
Connecting the system with mental health apps while keeping user data safe and private

## REFERENCES

[1]. J. Lu, V. E. Liong, X. Zhou, and J. Zhou,Learning compact binary face de- scriptor for face recognition, IEEE transactions on pattern analysis and machine intelligence, vol. 37, no. 10, pp. 2041 2056, 2015.
[2]. K. He, X. Zhang, S. Ren, and J. Sun Deep residual learning for image recognition in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770778.
[3]. B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba, Learning deep features for discriminative localization, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2921
[4]. I. Goodfellow et al., “Challenges in representation learning: A report on three machine learning contests,” Neural Networks, vol. 64, pp. 59–63, 2015.
[5]. S. Li and W. Deng, “Reliable Crowdsourcing and Deep Locality Preserving Learning for Expression Recognition in the Wild,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jul. 2017, pp. 2852–2861.