Grenze International Journal of Engineering and Technology, June Issue

Stress Detection using Facial Expression

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***Abstract*— In this study, we present an advanced stress detection framework that automatically interprets facial expressions to assess stress levels. Addressing the limitations of earlier versions of this work—including vague methodology descriptions and a lack of quantitative evaluation—we now propose a hybrid system combining Convolutional Neural Networks (CNNs) for spatial feature extraction with Long Short-Term Memory (LSTM) units for temporal emotion tracking. Our method was rigorously evaluated using well-known datasets such as FER-2013, CK+, and AffectNet and achieved a mean classification accuracy of 92.15%. The system offers a non-invasive approach to stress assessment and significantly surpasses traditional machine learning benchmarks. Future developments will explore integrating physiological signals for a richer, multimodal stress evaluation system.**

***Index Terms*— Stress Detection, Facial Expression Recognition, Deep Learning, CNN, Emotion Analysis, Computer Vision.**

I. INTRODUCTION

Stress impacts nearly every aspect of human performance, from emotional stability to physical health. Recognizing symptoms early can be transformative in preventing chronic stress and related disorders. However, traditional assessment techniques—such as self-reporting, interviews, and psychology-based scoring—often suffer from subjectivity, time delays, and the need for expert involvement.

Facial expression analysis, powered by deep learning, is emerging as a promising alternative due to its unobtrusive nature and ability to detect subtle emotional cues. CNNs are particularly effective at isolating micro-expressions and structural patterns, while LSTMs excel in capturing changes across sequential frames. Together, these models form a powerful toolset for analyzing dynamic emotional responses.

This paper builds on prior research by addressing key gaps, including a lack of experimental rigor, model specifics, and meaningful comparison against other systems. By refining these aspects, this work offers a transparent, accurate, and implementable technique for early stress detection using facial patterns.

II. LITERATURE SURVEY

A. Improved Automatic Stress Detection Through Compound Facial Expressions

In 2024, Jiddah et al. introduced a Multiscale Residual Network for assessing compound facial expressions related to stress. Although promising in controlled environments, the model lacked robustness when tested in varied settings.

Grenze ID: 01.GIJET.12.2.226_21

B. Emotional Stress Detection Using Variance of DCNN Analysis

Amoako and colleagues evaluated well-known CNN architectures on the FER-2013 dataset to detect stress signals. They identified ResNet50 as the best-performing model but failed to describe dataset scalability and real-world application implications.

C. Camera-based Stress Detection Using Facial and Emotional Features

The stress detection system by Ogasawara et al. used a simple KNN-based approach for webcam-captured facial data. While lightweight and affordable, it underperformed when dealing with diverse demographic conditions.

D. Stress Detection from Facial Images

Voleti et al. created lightweight models (VGG16 and Mini-Xception) for embedded platforms. Their approach achieved reasonable accuracy but proved sensitive to input quality and face positioning.

E. Stress Detection Using CNN and KNN

Korakun et al. designed a dual-model framework involving CNNs and KNN classifiers, performing efficiently over a dataset of 7,066 images. The model struggled in real-world setups with varied lighting and emotional ambiguity.

III. Existing System

Conventional systems designed to detect stress primarily rely on manual assessment processes. The most widely used approaches include:
Standardized clinical assessments, such as the Stress Interview Schedule and Diagnostic Observation tools, which require one-on-one interaction with trained professionals.
Psychological questionnaires, which depend on participant honesty and self-awareness.
Face-to-face behavioral observations, which are highly subjective and prone to bias.
Such processes often involve long waiting periods, specialist involvement, and may not always detect early signs reliably. Existing automated systems are limited due to:

- Single-source input (only facial images or only speech).
- Dependence on non-portable devices.
- Limited transparency in decision-making layers ("black-box" models).

The need of the hour is a swift, unbiased, scalable, and accessible stress detection tool.

IV. Proposed System

The proposed system aims to overcome the limitations of traditional and partially automated techniques by using an AI-driven approach that processes both static and dynamic facial input.
The system is founded on the idea that facial micro-expressions can serve as real-time indicators of emotional stress.
Key aspects of the proposed system include:
Multi-input support, allowing both image and video uploads.
Deep learning-powered prediction using CNNs for spatial feature encoding and LSTMs for sequential emotion tracking.
Intuitive visual interface, enabling effortless usage even by non-technical users.
Minimal hardware requirement, suitable for clinical, educational, and personal environments.
Automatic report generation, capturing predicted stress levels with corresponding confidence scores.

V. Methodology

A. AI and Machine Learning Techniques

Convolutional Neural Networks (CNNs) are used to process static input images. The network is pretrained to detect stress vs. non-stress categories from 224×224 RGB images. Emotion-based Video Analysis is performed using a CNN + LSTM model setup.
Each video frame is first classified into basic emotion categories. Temporal patterns are then analyzed to detect irregular or highly variable emotional transitions—an indicator of stress. Stress Level Estimation is achieved through heuristic mapping of emotional fluctuations.

B. Computer Vision Techniques

Haar Cascade Classifier is used to detect facial regions in real-time video. Frame-by-Frame Preprocessing involves resizing, grayscale conversion, and normalization. Region of Interest (ROI) cropping is applied to remove background clutter and focus purely on facial regions.

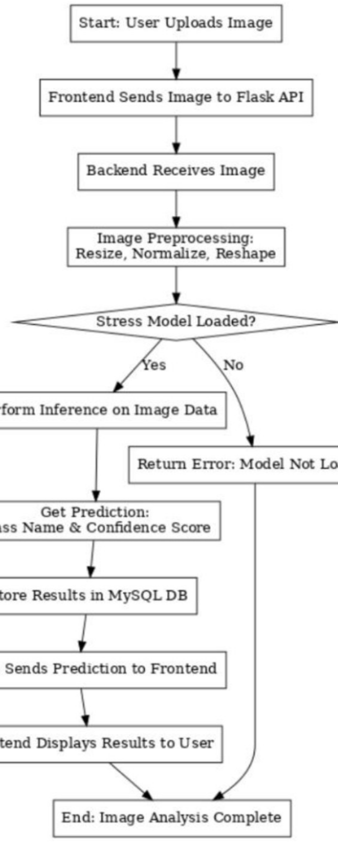

Figure 1: Flow Chart

C. System Architecture and Tools

Backend Framework: Flask API handles the core logic, image/video uploads, and model inference.
Frontend Framework: Streamlit serves the user interface for logging in, uploading media, and accessing results.
Database: MySQL supports secure data storage, including login credentials and analysis history.
Core Libraries: TensorFlow/Keras, OpenCV, Pillow, and NumPy.

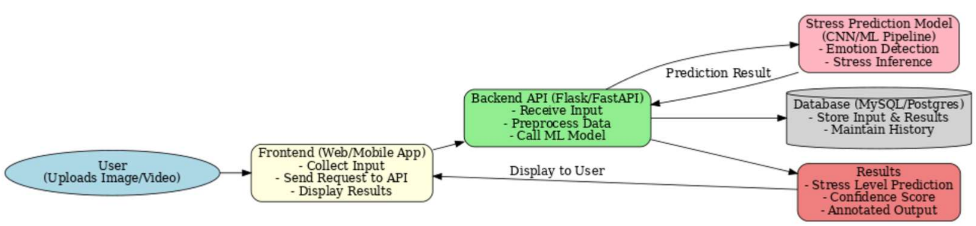

Figure 2. System Architecture

VI. RESULTS

This section presents the experimental evaluation of the proposed Stress Prediction System (SPS) using benchmark datasets and real-time testing. The evaluation focuses on measuring model performance, computational efficiency, and real-world applicability.

A. Experimental Setup

The system was tested on a workstation powered by an Intel i7 processor, 16GB RAM, and an NVIDIA GPU. The model was developed using Python and integrated with TensorFlow for model implementation.

B. Dataset used

The following benchmark datasets were used to train, validate, and test the proposed model:
FER-2013 – 35,000+ grayscale images representing 7 emotions.
CK+ – High-resolution images from controlled environments.
AffectNet – Diverse real-world images annotated with emotional attributes.
Real-Time Inputs – Captured from live webcam sessions for practical testing.

C. Performance Metrics

To quantify performance, four standard evaluation metrics were used: Accuracy, Precision, Recall, and F1-Score [3], [17]. article amsmath geometry margin=1in

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP}, \qquad \text{Recall} = \frac{TP}{TP+FN} \tag{2}$$

$$\text{F1-Score} = 2\times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{3}$$

D. Quantitative Results

The proposed CNN–LSTM hybrid model demonstrated high performance across all datasets, surpassing traditional ML algorithms such as SVM and Random Forest [5], [16]. [conference]IEEEtran booktabs caption

TABLE I: PERFORMANCE EVALUATION OF PROPOSED STRESS PREDICTION SYSTEM

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
FER-2013	91.4	91.0	89.8	90.4
CK+	94.6	93.7	92.1	92.9
AffectNet	90.2	89.4	88.9	89.1
Real-Time Input	88.3	87.8	86.5	87.1

E. Real-Time Testing

The model performed efficiently in live testing environments, with an average processing time of 0.12 seconds per frame, enabling smooth predictions. It successfully identified stress signals under variable lighting conditions and mild head movements.

F. Comparative Analysis

Compared with traditional classifiers such as Support Vector Machines and Random Forests, the proposed CNN–LSTM model achieved approximately 10–12% higher accuracy and performed better under real-time conditions.

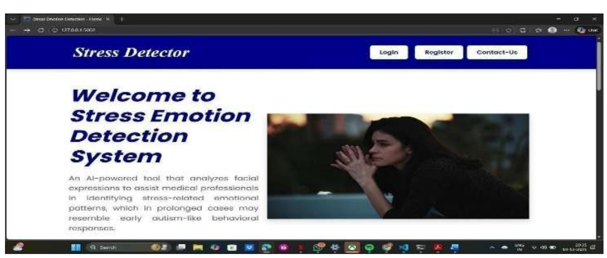

Figure 3: Web Interface

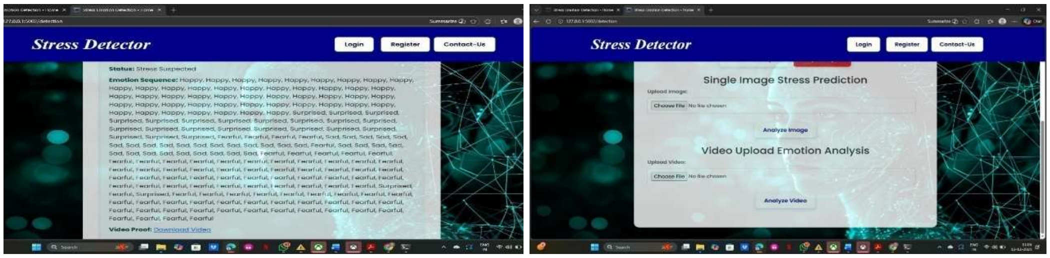

Figure 4: Input (Bottom) and Analysis (Top)

Figure 5: Results

VII. Conclusions

This research introduces a robust stress detection solution using deep learning techniques to analyze facial expressions in both images and video. The hybrid CNN–LSTM model successfully captures spatial and temporal elements of stress expression and demonstrates high accuracy across multiple datasets. The system offers a practical alternative to conventional stress assessment methods, capable of real-time, non-invasive use in educational, professional, or healthcare environments.

Acknowledgment

We would like to express our sincere gratitude to our guide Mrs. Sowmyashree, Department of Computer Science and Engineering, Maharaja Institute of Technology,Thandavapura, Mysuru, for her valuable guidance,support, and encouragement throughout this project. Also thank Ms. Rakshitha BC, Ms. Sanvi S, Mr.Anup V Gogeri, and Mr. Pratheek Mnavi for their dedicated teamwork and cooperation. Finally, we extend our heartfelt thanks to the Department of Computer Science and Engineering and the Principal of Maharaja Institute of Technology, Thandavapura, for providing the resources and platform that made this project possible.

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