STREFIE

Powered By Solh



Real-Time Stress Detection through Facial Recognition

Powered by Deep Learning, Convolutional Neural Networks (CNN) & Flask

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Technology Stack & Validation References

1. Introduction

The Streffie Stress Detector is an AI-powered, real-time stress monitoring platform that leverages facial recognition, facial landmark analysis, and deep learning to derive stress-related behavioural indicators directly from live video streams.

Engineered as a non-invasive wellness and behavioural analytics solution, the system identifies stressassociated facial patterns through advanced computer vision and machine learning, requiring no specialised hardware or physical contact with the user.

Technical Approach

The platform integrates a complementary set of techniques to deliver robust, real-time stress estimation:

Deep learning–based emotion recognition	Facial landmark tracking	Facial muscle movement analysis	Real-time video processing	Rule-based stress scoring

Core Objectives

The system has been purpose-built to provide:

Real-time stress awareness	Continuous behavioural monitoring	Non-contact stress estimation	Scalable wellness analytics

2. Technology Stack & Libraries

The solution is built on a mature, industry-standard open-source stack, ensuring reliability, maintainability, and ease of deployment.

- **Keras:** Deep learning model development
- **TensorFlow (backend):** CNN model training and inference
- **OpenCV:** Real-time video capture and frame processing
- **Dlib:** Facial landmark detection
- **imutils:** Facial processing utilities
- **Flask:** Real-time web deployment
- **NumPy:** Numerical computation

3. Core AI Architecture

The platform employs a hybrid AI architecture that combines deep learning–based emotion recognition with geometric facial landmark analysis.

CNN-Based Emotion Recognition Engine

At the heart of the system is a Convolutional Neural Network (CNN) trained on facial emotion datasets to recognise the emotional states most closely associated with stress.

Emotion Classes Recognised:

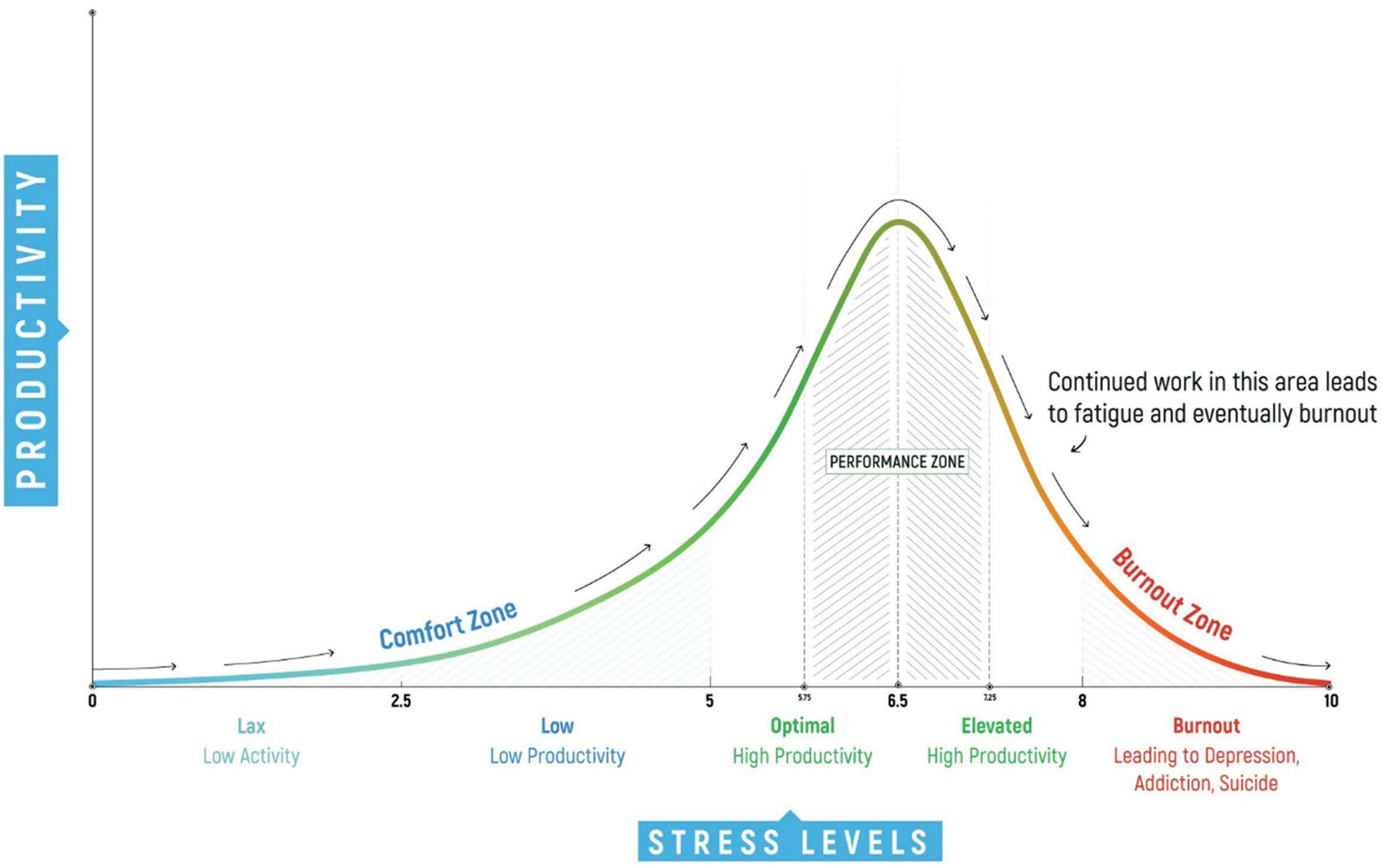
Angry	Disgust	Scared	Happy	Sad	Surprised	Neutral

Stress Scale Classification

Detected emotional and behavioural signals are mapped to a normalised stress index, classified across four tiers:

0 - 2.5	2.6 -5.0	5.1 - 6.5	6.6 - 8	8.1 - 10
Very Low	**Lax/Low**	**Optimal**	**Elevated**	**Burnout**

Presentation on graph:



The stress score is updated dynamically in real time throughout the facial analysis process.

4. Training Dataset

The emotion recognition model was trained on the **FER2013 dataset** (Kaggle), a widely adopted benchmark for facial emotion classification research.

- Total Images: 33,887
- Image Type: Grayscale
- Resolution: 48 × 48 pixels
- Emotion Categories: 7

Reference: FER2013 Dataset - Kaggle

Model Training Methodology

During training, the model learns to identify the fine-grained facial features that correlate with stress and emotional state, including:

- ☑ Facial texture patterns
- ☑ Eye tension
- ☑ Brow contraction
- ☑ Lip structure changes
- ☑ Facial muscular activation
- ☑ Expression geometry

5. Facial Landmark Detection

The system applies Dlib's 68-point facial landmark model for real-time facial movement analysis. The detector precisely localises:

Eyebrows	Eyes	Nose	Lips	Jawline	Facial contours

These landmarks enable measurement of:

Eyebrow tension	Lip compression	Jaw movement	Eye openness variability

6. Real-Time Stress Monitoring Pipeline

Each frame is processed through a sequential, end-to-end pipeline that transforms raw video input into an actionable stress score:

Step 1. **Video Acquisition** - Live capture via OpenCV

Step 2. **Face Detection** - Isolation of the facial region within each frame

Step 3. **Landmark Extraction** - 68-point mapping using Dlib

Step 4. **Emotion Prediction** - Classification via the trained CNN

Step 5. **Facial Movement Analysis** - Quantification of tension and micro-movements

Step 6. **Stress Score Calculation** - Fusion of emotional and geometric signals

Step 7. **Real-Time Visualisation** - Live output rendered through Flask and OpenCV

7. Research Validation

The methodology underpinning the Streffie platform is grounded in peer-reviewed academic research that validates facial-image and landmark-based stress estimation.

Stress Recognition Using Face Images and Facial Landmarks

This study validated facial landmark–based stress estimation, reporting classification accuracy of up to 92%, demonstrating the viability of the approach adopted by Streffie.

Reference: ResearchGate - Stress Recognition Using Face Images and Facial Landmarks

Deep Learning–Based Stress Recognition Using Facial Features

Published in a peer-reviewed sensors journal, this research corroborates the use of deep learning on facial features for reliable stress recognition.

Reference: ResearchGate - Stress Recognition Using Face Images and Facial Landmarks

Multimodal Stress Detection Using Facial Landmarks and Biometric Signals

This work explores the integration of facial landmarks with complementary biometric signals, reinforcing the scientific foundation for landmark-driven stress detection.

Reference: arXiv - Multimodal Stress Detection

8. System Strengths & Limitations

Key Strengths

- Real-time processing
- Non-invasive monitoring
- Compatibility with standard webcams
- No wearable or specialised hardware required
- Lightweight, low-overhead deployment
- Scalable, web-based architecture
- Support for continuous, ongoing monitoring

Limitations & Responsible Positioning

Stress is a complex psychological and physiological condition that cannot be measured definitively through facial expression alone. Accuracy may therefore vary depending on a range of environmental and individual factors, including:

Lighting conditions	Camera quality	Facial visibility	User movement	Expression suppression	Cultural differences in emotional expression

Important: System outputs should be interpreted as “AI-estimated stress indicators” and not as a clinical diagnosis.

While facial AI is not yet regarded as a standalone clinical diagnostic tool for stress disorders, it is increasingly adopted across industry as a decision-support and wellness-monitoring technology.

9. Real-World Validation & Industry Adoption

The Streffie approach is consistent with technologies already deployed and studied across healthcare, automotive safety, telemedicine, and regulatory contexts worldwide.

Healthcare & Hospital Research Adoption

ICU Patient Monitoring - Yokohama City University

Researchers have investigated AI-based facial monitoring systems within ICU environments to support continuous patient observation and the early detection of:

- Distress
- Agitation
- Emotional instabilit
- High-risk patient behaviour

Reference: Capgemini - Unlocking Facial Recognition Technology in Healthcare

University of Colorado - AI Facial Analytics

Researchers applied AI - based facial analysis, using advanced facial imaging and machine learning, to identify:

- Behavioural patterns
- Medical indicators
- Genetic-disorder characteristics

Reference: Capgemini - Unlocking Facial Recognition Technology in Healthcare

Mental Health & Telemedicine Applications

Facial AI technologies are increasingly explored across mental-health and telemedicine settings for:

- Emotional state monitoring
- Depression analysis
- Anxiety detection
- Telemedicine support
- Behavioural wellness tracking

Research demonstrates that facial behaviour patterns can meaningfully support AI-assisted emotional and stress estimation systems.

Reference: PMC - Facial Behaviour & AI-Assisted Stress Estimation

Driver Monitoring Systems (Commercial Deployment)

Driver Monitoring Systems (DMS) represent one of the strongest commercial validations of facial stress and fatigue detection. Modern DMS platforms combine:

- Facial landmarks
- Eye tracking
- Blink detection
- Head-pose estimation
- Facial fatigue indicators

These signals are used to detect driver fatigue, stress, cognitive overload, and distraction, and are already integrated into automotive safety platforms worldwide.

Reference: MDPI Sensors - Driver Monitoring Systems

Facial Emotion Recognition in Healthcare

Healthcare and wellness providers increasingly deploy facial emotion recognition for patient emotional monitoring, wellness tracking, telehealth support, behavioural analytics, and human-machine interaction. The industry consistently positions these systems as “AI-assisted behavioural and emotional analytics” rather than direct medical diagnosis.

Reference: MorphCast - Face Emotion Recognition in Healthcare

European Regulatory Recognition

The European Data Protection Board (EDPB) formally recognises Facial Emotion Recognition (FER) as an emerging AI technology area. Its reports acknowledge the use of eyebrow movement, eye behaviour, facial landmarks, lip movement, and facial geometry for emotional and behavioural inference.

Reference: EDPS - TechDispatch on Facial Emotion Recognition

Research Community Validation

Contemporary scientific research increasingly classifies facial stress and emotion recognition under the fields of Affective Computing, Digital Biomarkers, Behavioural AI, Emotional AI, and AI-assisted Wellness Monitoring. Modern research architectures commonly combine CNN-based facial analysis, facial landmark tracking, temporal facial behaviour analysis, and real-time emotion recognition for stressrelated behavioural estimation - precisely the combination implemented within Streffie.

Reference: ScienceDirect - Facial Stress & Emotion Recognition Research

10. Alignment with the Streffie Architecture

The current Streffie implementation aligns closely with established research and industry practice. Its core components include:

- CNN-based emotion recognition
- Dlib 68-point facial landmarks
- OpenCV real-time facial tracking
- Facial movement analysis
- Emotion-to-stress inference logic
- Real-time visualisation through Flask

These technologies are widely adopted across computer vision research, emotional AI systems, driver monitoring systems, telemedicine platforms, and wellness analytics solutions.

Scientific Positioning

To remain aligned with current scientific consensus and industry adoption, Streffie should be positioned as:

- An AI-assisted stress awareness system
- A behavioural wellness analytics platform
- An emotional state estimation framework
- A non-invasive monitoring technology
- A preventive wellness support system

Rather than as:

- A clinical diagnostic tool
- A psychiatric evaluation platform
- A medical-grade stress diagnosis system

This positioning is fully consistent with prevailing scientific consensus and industry adoption trends.

11. Conclusion

Facial landmark analysis and AI-driven emotional analytics are now globally recognised as promising technologies for non-invasive behavioural monitoring and stress estimation.

Research institutions, healthcare systems, automotive safety companies, telemedicine providers, and emotional AI platforms are increasingly adopting similar architectures for wellness monitoring, fatigue detection, emotional analytics, behavioural observation, and human-state estimation.

The Streffie framework is firmly aligned with these emerging global trends and offers a scalable foundation for future AI-assisted wellness and behavioural intelligence systems. The platform delivers a scalable, non-invasive stress awareness solution well suited to wellness platforms, educational

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