Leveraging Machine Learning for Emotion Detection and Real-Time Implementation of Calming Techniques to Enhance Mental Well-Being

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Abstract: This paper presents a machine learning system that was trained on the FER2013 dataset to achieve emotional state detection with stress recognition as the main focus. It is built using OpenCV, Keras, and TensorFlow, and the solution provides a practical use of it in high-stress situations like schools and offices, providing automated and instant help. If perceived stress is detected, the system will trigger relaxation techniques like guided breathing and progressive muscle relaxation. The system achieved 81.78% accuracy in classifying seven emotions. Although the model has good performance at recognizing clear emotions, such as happiness and surprise, there are problems in precisely determining more subtle expressions like stress.

Key Words: emotion detection; convolutional neural network; Stress Recognition; Real-Time Intervention; Mental Well-Being; FER2013 Dataset; Facial Emotion Recognition (FER); Calming Techniques; OpenCV; TensorFlow; Progressive Muscle Relaxation;

1. INTRODUCTION

AI-based emotional monitoring technology using affective computing detects emotions immediately during the assessment process by offering advanced help beyond basic mental health evaluation standards (Calvo & D'Mello, 2010). Behavioral and physical data analysis from these systems enables distress detection which provides relief strategies but needs ethical review for proper implementation (Picard 2003). Artificial intelligence mental health tools need proper ethical management together with fair operation while delivering swift resolution to reach success. AI mental health support systems utilize facial and body signal recognition to trigger programmed calming functions.

The research investigates AI camera systems that recognize school and workplace settings because those areas have population members who experience ongoing stress and anxiety. The network-based tools provide immediate emotional assistance by adjusting the pace of breathing and playing audiovisual elements which support better work performance. Artificial

Intelligence combines with mental wellness to deliver assistance earlier than standard self-report systems allowing the problems to intensify through this new approach. AI software development aims to detect negative emotions by monitoring psychological signals to activate protection systems.

The study will only focus on the use of computer vision and machine learning algorithms to analyze emotional states. The system is designed to identify stress and negative emotions and trigger real-time interventions. The research will not focus on bigger issues of mental health disorders but rather on the emotional states of stress. The AI model will also be trained using a predefined dataset that does not include physiological data like pulse rate or blood pressure so that it will only analyze the visual and behavioral cues for emotion detection.

2. Facial Emotion Recognition

Research in Facial Emotion Recognition (FER) progresses through continuous studies that work on enhancing accuracy while achieving practical, real-world use. Na et al. (2023) present FacialNet, which combines UNet segmentation with EfficientNetB4 to reach 96.39% binary classification accuracy while obtaining good performance in detecting six emotions through segmentation-enhanced feature extraction. Mehendale had previously developed a two-level CNN structure that reached 96% accuracy, which questions the necessity of using FacialNet as an innovative technology.

Bhagyalakshmi and Mehendale (2023) increased the emotional scope of their analysis by including anger, fear, and confusion emotions through their CNN approach, which maintained 96% accuracy. The author stresses that dataset variety is equally important to the process of data grouping. Ballesteros et al. (2024) push this further by adding real-time emotion detection capabilities in video communication systems, which indicates that future FER technology might use dynamic adaptive approaches over conventional static image classification.

3. Calming Techniques For Mental Well-Being

Hamdani et al. (2022) performed a systematic review and meta-analysis of 65 randomized controlled trials (RCTs) which included 8,009 adolescents, to evaluate the effect of relaxation techniques on distress, depression, and anxiety. Relaxation techniques demonstrated the most significant benefit for treating anxiety, whereas they produced moderate results for distress management but showed less effectiveness in treating depression.

The research by Khir et al. (2024) expanded its analysis to adult participants by examining 46 PMR-related studies that included 3,400 participants. The analysis demonstrated PMR therapy leads to significant stress reduction and decreased symptoms of depression and anxiety. To better understand why these interventions work, Gu et al. (2016) examined the research findings regarding Mindfulness-Based Cognitive Therapy (MBCT) and Mindfulness-Based Stress Reduction (MBSR). They discovered through their study that mental health benefits from mindfulness-based protocols through decreased rumination and emotional reactivity, which contribute to anxiety and depression.

4. AI-Driven Mental Health Techniques

AI is advancing in the field of mental health condition diagnosis and monitoring as well as treatment. AI is faster than traditional methods of data analysis and can be more accurate in analyzing large amounts of data, finding patterns, and predicting or forecasting symptoms. The ability to detect mental health problems sooner and more easily treat them could give doctors this capability. Baumeister et al. (2024) support this by indicating that AI-powered tools can give real-time insight into someone’s mental health with the use of wearable devices, apps, and digital assessment. These tools allow mood, behavior, and other indicators to be tracked, and personalized treatment becomes more available.

However, many still are not fully convinced. According to Warrier et al. (2023), the issues AI poses are ethical and practical challenges. The main problem is data privacy. Personal data that is fed into AI systems is much of the data, and there is a risk that it could be misused or accessed by someone who is not entitled to view the data. Another concern is bias. In particular, if the AI is trained on data that does not cover a large enough set of people, then its predictions may not be as accurate for some groups. In this version, Warrier et al. stressed the need for AI systems to be transparent and explain how they come to their decisions so users and clinicians can believe the results.

5. Facial Indications of Stress and Relabeling of FER2013

Stress-related facial expressions combine aspects of anger and concern, therefore causing tension in the facial area and furrowing across the browline, according to McEwen (2007). Research by Mueller et al. (2019) reveals that natural forehead self-touch gestures rise at higher emotional and cognitive stress levels, thus indicating stress regulation through face-touch behavior. Studies show that people with depressive symptoms show increased reactions to depressed facial expressions during times of mental stress (Chen et al., 2018). This particular case demonstrates that researchers should group the emotion labels in FER2013 to two classification groups namely, 'Stressed' and 'Not Stressed' based on established emotional expression research.

6. METHODOLOGY

6.1 Materials

This system used AI cameras with emotion detection algorithms based on OpenCV, Keras, and TensorFlow. The AI outputs were processed by a custom-built Python application that integrated them with pre-programmed calming techniques. Local storage was used to store the secure data of emotion data and system performance metrics to enable data privacy and efficient performance tracking.

6.2 Dataset

Table 1. Image Distribution

Category	Images
Angry	4953
Happy	8989
Neutral	6198
Sad	6077
Surprise	4002
Fear	5121
Disgust	547

The image distribution from the FER2013 dataset is presented in Table 1, where they were downloaded from Kaggle. The dataset consists of grayscale facial images in 7 emotion categories, which were then grouped into 2 categories, which are either "Stressed" or "Not Stressed," enabling binary classification. The emotions, Angry, Sad, and Fear are grouped in Stressed, while Neutral, Happy, and Surprise will be classified as "Not Stressed". Disgust emotion is excluded since it can affect the accuracy of the Not Stressed classification due to its low sample size. It was also applied to have an 80/20 train-test split for effective model training and evaluation.

6.3 Development of the Model

The model was built using Keras with a Convolutional Neural Network (CNN) and was trained using Kaggle's FER2013 dataset. Keras's ImageDataGenerator was used to add data augmentation techniques such as rescaling, rotation, zooming, and flipping. The architecture of CNN consists of many convolutional layers with growing filter size, max pooling and dropout layers, and a dense layer with a softmax layer as its classification part. It employs the technique of data augmentation to vary training data sets by randomly rotating, shifting and flipping images this avoids overfitting models with particular patterns of faces. It uses class weights to tackle the issue of class imbalance by paying adequate attention to the minority class ("Stressed") in training. Another difference with the model is that it monitors not solely the accuracy but AUC (Area Under the ROC Curve) that gives a better picture of the performance on imbalanced data. Notably, the training is based on AdamW, an adaptive optimiser, which stops weight decay leading to improved generalisation. The decision will aid the convergence and minimize overfitting and in advancing fair and stable learning on both classes.

6.4 Testing and Evaluation of the Model

Evaluation of the trained CNN model was done on the test set from the FER2013 dataset. The performance of the model was assessed using a confusion matrix and a classification report. To make it clearer, accuracies were determined in percentages in class and in total. A heatmap was used to plot a confusion matrix to represent how well the model performs in terms of its accuracy and what areas it tends to misclassify in the seven emotion categories.

7. RESULTS AND DISCUSSION

7.1. Emotion Detection Test

7.1.1. Not Stressed

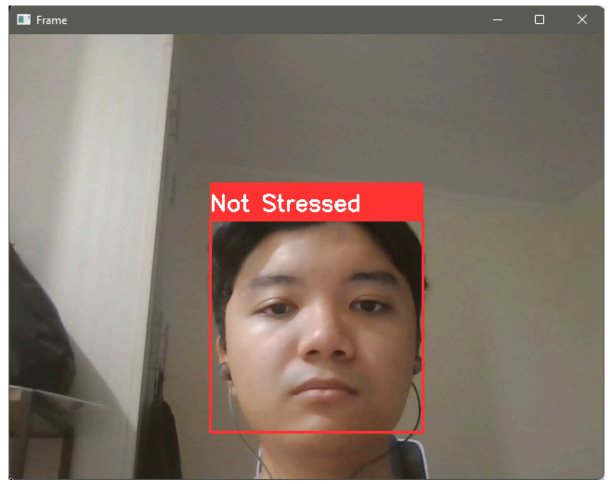

Fig. 1. Not Stressed Real-Time Classification Result

7.1.2. Stressed

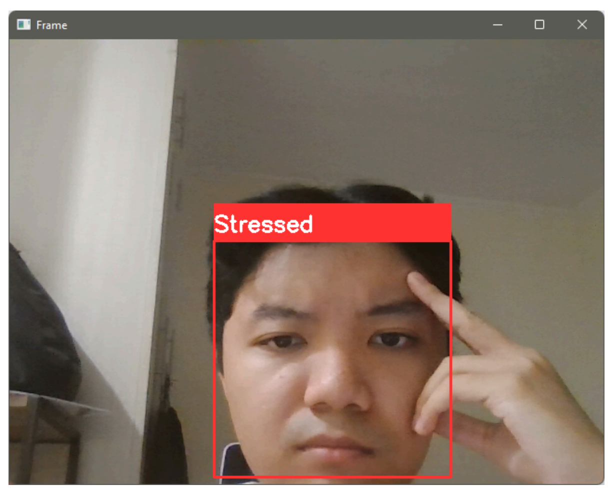

Fig 2. (a) Happiness; (b) Anger; (c) Surprise; (d) Stressed

7.2. Emotion Test in Different Angles

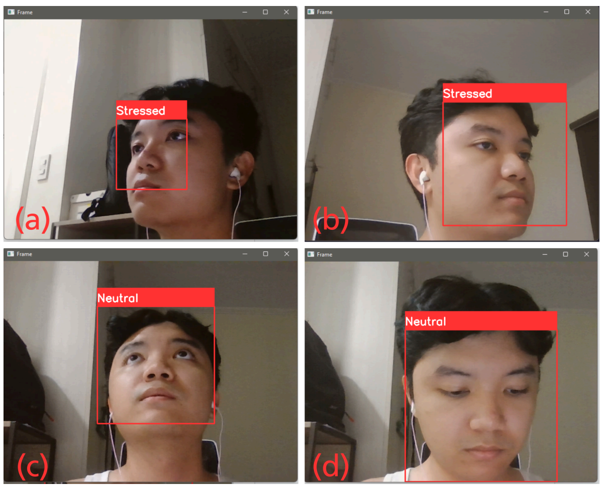

Fig 3. (a) Left Side Angle; (b) Right Side Angle; (c) Bottom View Angle; (d) Top View Angle

7.3 Calming Intervention Test

6.3.1. Breathing Techniques

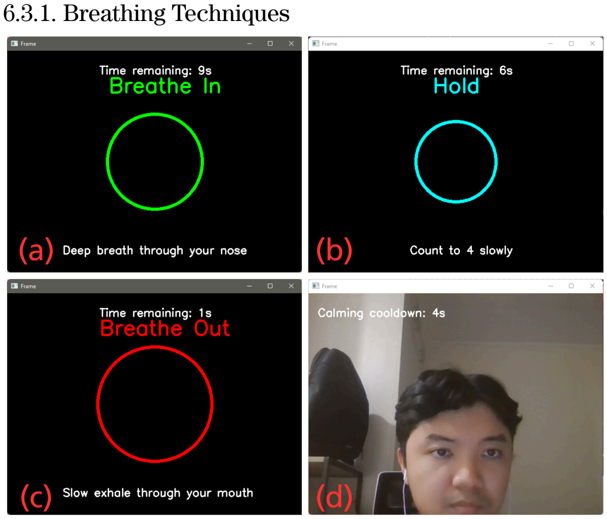

Fig 4. (a) Breath In Period; (b) Hold Breath Period; (c) Breathe Out Period; (d) Cooldown Period

7.3.2. Progressive Muscle Relaxation

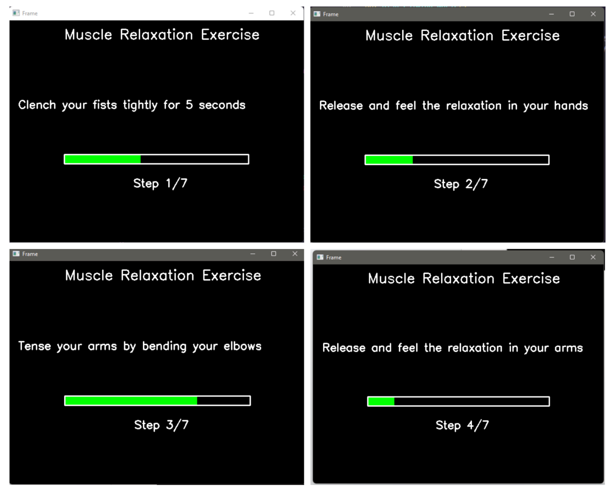

Fig 5. Steps 1-4 of the Muscle Relaxation Manual

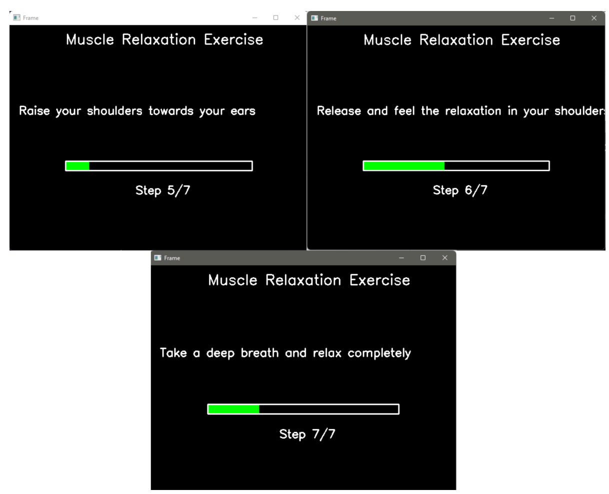

Fig 6. Steps 5-7 of the Muscle Relaxation Manual

7.4. Performance Evaluation Test

7.4.1. Confusion Matrix

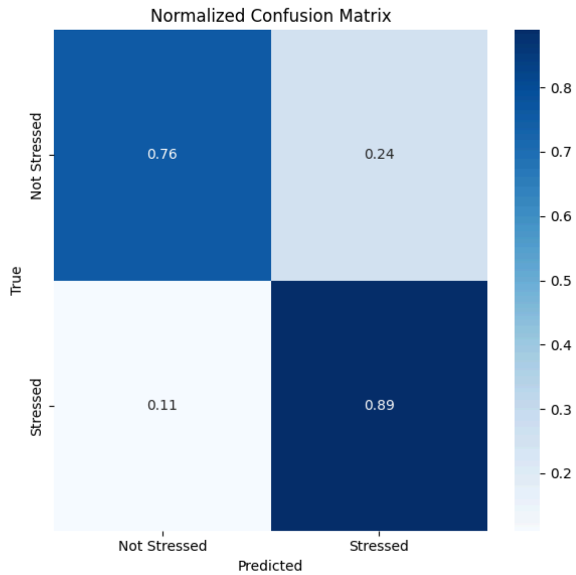

Fig. 7. Confusion Matrix Result

7.4.2. F1-Score

Table 2. F1-score Result

Class	Accuracy	Precision	Recall	F1-Score	Suppor
Not Stressed	75.75%	89.05%	75.75%	81.86%	2878
Stressed	88.94%	75.53%	88.94%	81.69%	2423
Total	81.78%	82.87%	81.78%	81.78%	5301

7.4.3. Recall & AUC Result

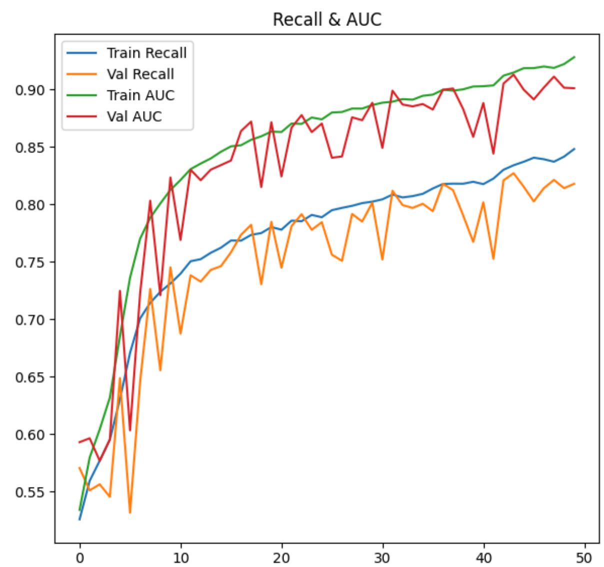

Fig. 8. Recall & AUC (Train & Val) Result

7.4.4 Detection Response Time

Table 3. Detection Response Time Result

Steps	Response Time Per Step
1	18ms/step
2	19ms/step
3	18ms/step
4	18ms/step
5	19ms/step
6	17ms/step
7	17ms/step

8	17ms/step
9	18ms/step
10	19ms/step

8. CONCLUSIONS

The study explores possible machine-learning-based systems for emotion detection and calming activities in real-time. The system identifies emotional states with a reasonable level of accuracy, applying convolutional neural networks (CNNs) in TensorFlow and real-time preprocessing in OpenCV. An overall accuracy of 81.78% highlights the success and difficult process of improving recognition rates across different emotional classes.

Calming activities like guided breathing and relaxation are possible applications of machine learning to advance mental health. This warrants the real-time counter-responses to negative emotional states, thus introducing the idea of automated mental health assistance supported in distressing environments like schools and workplaces. The system does identify a few emotions with limitations, such as Stressed, however performs quite well in identifying Happy and Surprise emotions, enforcing the need for quality and diversity in datasets.

While the present version of the system is looking promising, there are still several challenges ahead, which must be overcome to make the system robust and generalizable. The model can be made more accurate by training on richer datasets that are more diverse in terms of persons and expressions of emotional cues. Furthermore, transfer learning and fine-tuning on pre-trained models could also be useful to improve classification scores and reduce bias in this experimental setup.

The research demonstrates a practical use of emotion detection and intervention systems; thus, bridging the artificial intelligence technology with mental health enhancement. With further development, these emerging systems could revolutionize the delivery of real-time mental health support into something more ubiquitous and responsive to users' emotional states. Some of the near-future directions will aim to enhance model accuracy, review the range of emotions detectable, and work toward the betterment of interventions.

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