Stress Detection from Facial Expressions

Deep Learning-Based Emotion Recognition System (KMU-FED Dataset)

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1. Introduction and Goals

1.1 Project Context

Stress Detection from Facial Expressions is a deep learning application that analyzes facial images to detect emotional stress using the KMU-FED dataset. The system uses a Convolutional Neural Network (CNN) for emotion classification and maps negative emotions (anger, fear, sadness) to stress states.

This project is a re-implementation of the methodology described in "Detecting Negative Emotional Stress Based on Facial Expression in Real Time" (Li et al., 2019). The original paper demonstrated that facial expression analysis provides a non-intrusive method for stress detection applicable in healthcare monitoring, driver assistance systems, and workplace well-being tools.

The implementation uses TensorFlow/Keras for model development and includes an enhanced inference system with smart detection logic for handling ambiguous cases where individual emotion confidence is low but combined stress indicators are elevated.

1.2 Project Objectives

The main objectives of this project were:

- Reproduce the stress detection methodology from the original research paper
- Train a CNN-based emotion recognition model achieving >90% accuracy
- Map predicted emotions to binary stress/non-stress categories
- Develop enhanced inference logic for edge case handling
- Achieve high recall for stress detection to minimize missed cases

2. Materials and Methods

2.1 Dataset Characterization

Data Source: KMU-FED (Korea Maritime University Facial Expression Dataset) provides grayscale facial images categorized into six basic emotions. After data augmentation (horizontal flipping, small rotations), the dataset contains 3,318 samples split into training (70%), validation (15%), and test (15%) sets.

Property	Description
Source	Korea Maritime University (KMU-FED)
Data Type	Static grayscale facial images
Total Samples	3,318 images (after augmentation)
Image Size	224 x 224 pixels
Classes	Anger, Disgust, Fear, Happiness, Sadness, Surprise

Table 1: Dataset characteristics

Stress Mapping: Following the original paper, emotions are grouped into **stress-related** (Anger, Fear, Sadness) and **non-stress** (Happiness, Surprise, Disgust) categories. While disgust is technically negative, it is less associated with psychological stress in the literature.

2.2 Methods and Tools

2.2.1 Technology Stack

Python 3.10	TensorFlow 2.10+	OpenCV 4.5+	scikit-learn 1.0+

2.2.2 CNN Architecture

The model consists of 4 convolutional blocks followed by 2 dense layers:

- 4 Convolutional blocks with increasing filters (32, 64, 128, 256)
- Each block: Conv2D, BatchNorm, ReLU, MaxPool, Dropout
- Dense layers: 512 and 256 neurons with 50% dropout
- L2 regularization (0.001) and label smoothing (0.1)
- Total parameters: approximately 2.5 million

2.2.3 Training Configuration

Parameters: Adam optimizer (lr=0.0001), categorical cross-entropy with label smoothing, early stopping (patience=12), class weights with 20% fear reduction to prevent over-prediction. Training employed data augmentation (horizontal flip, 5 degree rotation).

2.2.4 Enhanced Inference System

The inference module implements smart detection rules for ambiguous cases: (1) Low confidence + high combined stress probability triggers STRESS, (2) Non-stress prediction but combined stress of 40% or higher triggers Override to STRESS, (3) Any individual stress emotion above 18% triggers STRESS. This approach catches edge cases where the model is uncertain but stress indicators are present.

3. Results

3.1 Training Behavior

The model trained for 59 epochs before early stopping. Training accuracy reached 98.19% with validation accuracy of 92.97%. The loss curves show healthy convergence without significant overfitting.

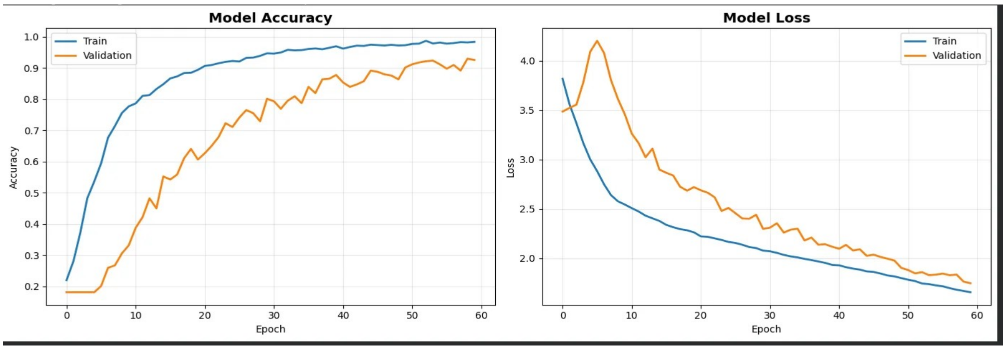

Figure 1: Training and validation accuracy (left) and loss (right) over epochs

3.2 Emotion Classification Results

3.2.1 Overall Performance

On the held-out test set of 498 images, the model achieved:

Metric	Value
Test Accuracy	92.77%
Weighted F1-Score	92.79%
Macro F1-Score	93.11%

Table 2: Overall test performance metrics

3.2.2 Per-Class Performance

Emotion	Precision	Recall	F1-Score	Category
Fear	81.82%	100.00%	90.00%	Stress
Anger	97.67%	94.38%	96.00%	Stress
Sadness	96.20%	93.83%	95.00%	Stress
Disgust	98.08%	94.44%	96.23%	Non-Stress
Happiness	91.67%	81.91%	86.52%	Non-Stress
Surprise	96.55%	93.33%	94.92%	Non-Stress

Table 3: Per-class performance metrics

All stress-related emotions achieved F1-scores above 90%. Notably, **fear achieved 100% recall**, ensuring no fear expressions are missed. The slight precision trade-off (81.82%) is acceptable since missing a stressed individual is worse than a false positive.

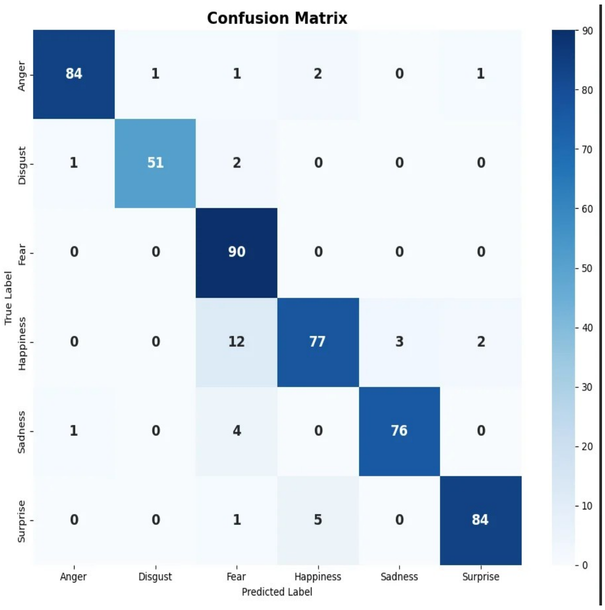

Figure 2: Confusion matrix for 6-class emotion classification

3.3 Stress Detection Results

When emotions are mapped to binary stress/non-stress categories, the system achieves **95.38% accuracy** with **98.46% stress recall**. Out of 260 stressed samples, only 4 were missed.

Class	Precision	Recall	F1-Score
Non-Stress	98.21%	92.02%	95.01%
Stress	93.09%	98.46%	95.70%

Table 4: Binary stress detection performance

3.4 Sample Predictions

High Confidence Detection: Figure 3 shows successful fear detection with 72.6% confidence. The combined stress probability (anger + fear + sadness) reaches 80.6%, clearly indicating stress.

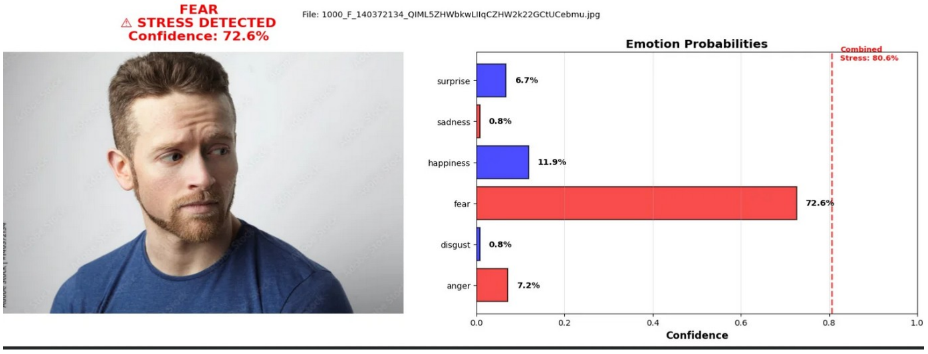

Figure 3: Fear detection with 72.6% confidence (Combined stress: 80.6%)

Enhanced Detection: Figure 4 demonstrates the smart detection system. Despite lower confidence (40.1%), the system correctly identifies stress because combined stress probability (51.1%) exceeds the override threshold.

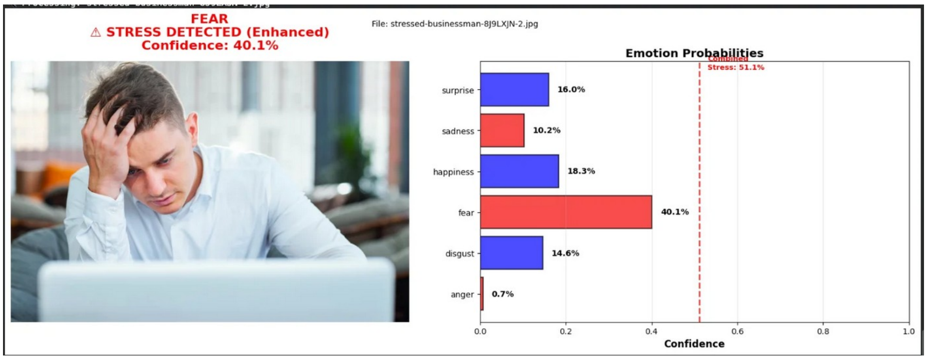

Figure 4: Enhanced stress detection with 40.1% confidence (Combined stress: 51.1%)

4. Conclusions

4.1 Achievement of Goals

This project successfully achieved all stated objectives. The implemented system demonstrates that facial expression analysis is a viable approach for automated stress detection.

Key Achievements:

- **92.77% emotion classification accuracy** exceeding the 90% target
- **95.38% stress detection accuracy** with 98.46% stress recall
- **100% fear recall** ensuring all fear expressions are detected
- All stress-related emotions achieved F1-scores above 90%
- Enhanced inference system successfully handles ambiguous cases

Critical Finding: The high stress recall (98.46%) means that out of 260 stressed individuals in the test set, only 4 were missed. This is crucial for practical applications where failing to detect stress could have serious consequences.

4.2 Limitations and Future Work

Limitations:

- Static images only; real applications may benefit from video/temporal analysis
- KMU-FED dataset may not capture full cultural diversity in expressions
- Subtle or masked emotions may not manifest in clear facial expressions

Future Enhancements:

- Transfer learning with VGGFace or ResNet for improved feature extraction
- LSTM integration for video-based temporal stress detection
- Multi-modal fusion with physiological signals (heart rate, skin conductance)
- Edge device deployment for real-time applications

5. Literature

1. Li, R., Liu, Z., Zhang, J., et al. (2019). *"Detecting Negative Emotional Stress Based on Facial Expression in Real Time."* IEEE 4th International Conference on Signal and Image Processing (ICSIP), Wuxi, China, pp. 430-434. DOI: 10.1109/SIPROCESS.2019.8868704