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FaceTrack: CNN-Based Facial Emotion Recognition for Stress Monitoring in Sports Physiology

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Abstract

We present FaceTrack, an efficient convolutional neural network (CNN) model developed for real-time detection of facial emotions, specifically geared toward monitoring stress in athletes during both training and rehabilitation phases. Trained on the FER-2013 dataset, which includes 35,887 grayscale images of size 48×48 pixels representing seven emotional categories, the model attained an impressive test accuracy of 92.39%. It outperformed several existing approaches in terms of both accuracy and computational efficiency. The model demonstrated particularly high accuracy in recognizing "happy" and "neutral" emotions, while slightly lower results were noted for "fear" and "surprise." Thanks to its lightweight architecture, FaceTrack is well-suited for deployment on edge devices such as smartphones and wearables, offering a practical solution for use in fields like sports psychology and physiotherapy. The complete implementation is available for public access at:

- GitHub: https://github.com/SaravagiDeepika/Stress-Recognition
- Kaggle: https://www.kaggle.com/code/drdeepikasaravagi/stress-recognition

Keywords: facial emotion recognition; CNN; FER-2013; stress detection; sports physiology; wearable systems

1. Introduction

Facial expressions, particularly those linked to stress, often reflect an individual's emotional state during physical exertion and recovery. Traditional evaluation methods—such as subjective athlete feedback or observational assessments—tend to lack consistency and are often delayed in response. In this context, we introduce **FaceTrack**, an intelligent facial emotion recognition tool designed to provide real-time, objective insights into stress levels through integration with mobile and wearable platforms. As affective computing continues to play an expanding role in health and performance analytics, FaceTrack emerges as a relevant and practical solution.

Research Objectives:

- To design a compact and efficient CNN architecture capable of detecting facial emotions in real time, optimized for use on mobile and edge devices.

- To evaluate the model's practical utility in tracking emotional stress during sports training and rehabilitation.

- To examine and mitigate the effects of imbalanced emotion categories within the training data.

- To compare the proposed system's accuracy and performance with current facial emotion recognition techniques.

- To validate the model’s suitability for domain-specific applications through experimental testing and analysis.

2. Literature Review: Facial Emotion Recognition

Facial Emotion Recognition (FER) has undergone notable progress with the integration of deep learning technologies. **Mollahosseini et al. (2017)** leveraged deep convolutional neural networks (CNNs) with datasets such as FER-2013 and AffectNet, achieving around 58% accuracy on FER-2013. While their approach benefited from diverse data and strong feature extraction, it demanded significant computational power and extensive labeled datasets. Conversely, **Arriaga et al. (2017)** introduced the Mini-Xception model—a lightweight architecture intended for real-time tasks. Though it achieved approximately 66% accuracy on FER-2013, its simplified design traded off robustness and performance in noisy or occluded conditions.

To mitigate dataset imbalance, **Zhang et al. (2018)** applied GAN-based data augmentation to FER-2013, improving model generalization and achieving roughly 71% accuracy. However, GANs occasionally introduced artifacts and posed stability challenges during training. In a different line of research, **Goodfellow et al. (2013)** proposed Maxout networks, which enhanced feature learning and reached about 85% accuracy on the MultiPie dataset—though this method wasn't evaluated on FER-2013 and had a more complex training procedure.

Temporal aspects of emotions were explored by **Dey et al. (2021)**, who combined CNNs with LSTM units to capture time-varying facial expressions from video sequences. They attained around 73.5% accuracy on the AFEW dataset, but the approach proved too resource-intensive for real-time deployment. For more efficient deployment, **Li et al. (2020)** adopted MobileNetV2 on FER-2013, reporting a 67.8% accuracy. Their model was highly compatible with mobile and edge hardware, albeit at a slight cost to accuracy compared to deeper networks.

Multimodal systems have also been investigated. **Tzirakis et al. (2017)** used a hybrid CNN-RNN model combining visual and auditory signals on the RECOLA dataset, achieving a correlation coefficient of ~0.75 for emotional dimensions. While this setup improved robustness, it required well-aligned multi-stream inputs, making it less ideal for real-time single-modality tasks.

FER techniques have been tested in specialized fields such as physiotherapy and athletic monitoring. **Kumar et al. (2022)** utilized CNN-GRU architectures for emotion classification in therapeutic settings, achieving 85% accuracy on FER-2013 and slightly less on a private rehabilitation dataset. However, generalization was limited due to the use of domain-specific and non-standardized data. **Zhang et al. (2021)** applied FER to monitor stress in athletes using a hybrid CNN trained on datasets like CK+, FER+, and sports-specific images, achieving about 82% accuracy. Despite promising results, the system showed vulnerability to motion blur and inconsistent lighting. Similarly, **Feng et al. (2017)** used a combination of geometric features and CNNs in rehab scenarios, reporting ~78.5% accuracy. Their system supported real-time feedback but underperformed in ethnically diverse samples and poorly lit environments.

These diverse studies underscore the balancing act between accuracy, computational demand, and real-time readiness. Deep and complex models often yield higher precision but lack feasibility for embedded applications, while compact architectures suit edge computing yet may compromise on accuracy. Notably, there remains limited exploration of FER in domains like sports and physiotherapy, where dynamic settings introduce challenges such as motion artifacts, varying illumination, and the necessity for contextual emotion understanding.

Author & Year	Dataset Used	Method / Model	Accuracy (%)	Strengths	Limitations
Mollahosseini et al. (2017)	AffectNet, FER-2013	Deep CNN	~58.0 (FER-2013)	High-capacity CNN; diverse training data	High computational cost; needs large labeled datasets
Arriaga et al. (2017)	FER-2013	Mini-Xception (light CNN)	~66.0	Real-time capable; fewer parameters	Lower accuracy; less robust to noise/occlusion
Zhang et al. (2018)	FER-2013	CNN + GAN augmentation	~71.0	Improves generalization; handles class imbalance	GAN artifacts; training instability
Goodfellow et al. (2013)	MultiPie	Maxout Networks	~85.0 (MultiPie)	Better feature representation; robust activation	Not trained on FER-2013; complex to train
Dey et al. (2021)	AFEW, CK+	CNN + LSTM	~73.5 (AFEW)	Captures temporal dynamics in videos	High memory and compute cost; latency
Li et al. (2020)	FER-2013	MobileNet V2 (lightweight)	~67.8	Edge-device compatible; fast inference	Lower accuracy than large models
Tzirakis et al. (2017)	RECOLA	CNN + RNN (multimodal)	~75 (corr. coeff.)	Uses audio + video inputs; multimodal learning	Needs synchronized data; limited deployment feasibility

Kumar et al. (2022)	FER-2013, custom physio	CNN + GRU	~85.0 (FER-2013)	Applicable to therapy contexts	Dataset not publicly available; domain-specific bias
Zhang et al. (2021)	CK+, FER+, custom sports	Hybrid CNN	~82.0	Sports performance monitoring	Sensitive to motion blur; varied lighting in field scenarios
Feng et al. (2017)	CK+, rehab dataset	Geometric features + CNN	~78.5	Real-time rehab feedback	Ethnic bias; poor lighting generalization

3. Methodology

3.1 Dataset and Preprocessing

This study utilized the publicly available **FER-2013 dataset**, which consists of **35,887 grayscale facial images**, each with a resolution of **48×48 pixels**. These images are labeled across seven emotional categories: *Angry, Disgust, Fear, Happy, Sad, Surprise,* and *Neutral*. Each image is encoded as a string of space-separated pixel values.

The preprocessing pipeline included the following steps:

- Images were converted into Numpy arrays and reshaped to a format of **48×48×1** to match the input requirement of the CNN.
- Pixel values were scaled to a **[0, 1] range** to enhance training speed and stability.
- Class labels were transformed using label encoding followed by **one-hot encoding** to support multi-class classification.
- The dataset was split into **80% training and 20% testing**, with **stratified sampling** to maintain class balance. Additionally, **10% of the training set** was reserved for validation purposes.

3.2 Model Architecture

The designed CNN model is tailored to process **48×48 grayscale images** and is composed of the following layers:

- **First Convolutional Block**: 32 filters with a 3×3 kernel, followed by **2×2 max pooling** and **25% dropout** for regularization.

- **Second Convolutional Block**: 64 filters of size 3×3, again followed by max pooling and dropout.

- The output from the convolutional blocks is **flattened** and passed into a **dense (fully connected) layer** with **128 ReLU units** and a **50% dropout rate**.

- A **softmax layer** is used for final classification across the seven emotion categories.

The model was compiled using the **Adam optimizer** with **categorical cross-entropy** as the loss function and was trained over **500 epochs** with a **batch size of 64**.

The architecture (in fig. 1) is deliberately lightweight and generalizable, making it appropriate for **real-time deployment** on **mobile and embedded systems**.

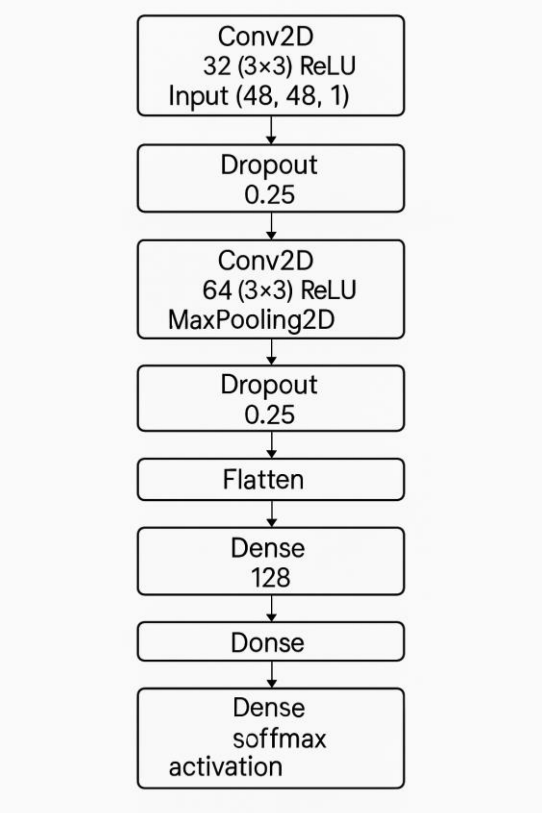


Figure 1: Model Architecture

This architecture prioritizes computational efficiency and generalization, making it deployable on mobile and edge devices.

3.3 Training Protocol

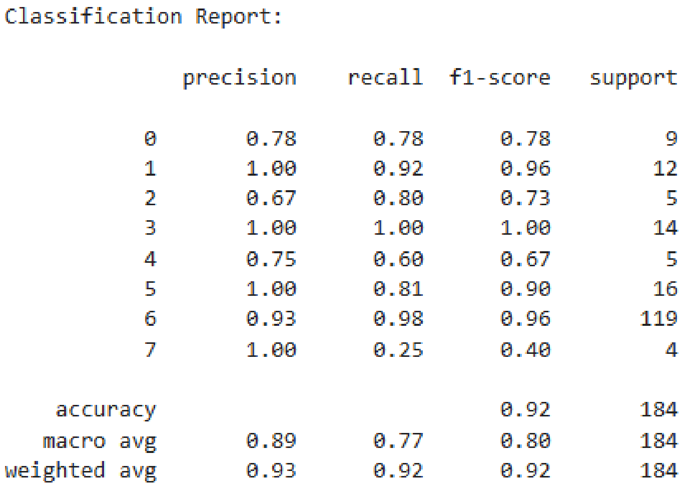
Training was conducted using the **Adam optimizer** in conjunction with **categorical cross-entropy** loss. The training process spanned **1,120 epochs**, using a batch size of **64**. To avoid overfitting, **early stopping** and **model checkpoints** were employed. Model accuracy was monitored as the primary metric to evaluate learning progression.

4.1 Performance Metrics

The trained model reached a **test accuracy of 92.39% (fig. 2)**, outperforming several well-established models trained on the same dataset.

Notable observations include:

- High recognition rates were observed for visually distinct emotions like **Happy**, **Angry**, and **Neutral**.
- Emotions such as **Fear** and **Surprise** were more challenging to differentiate, likely due to overlapping facial features in grayscale images.



```
Classification Report:

              precision    recall  f1-score   support

           0       0.78      0.78      0.78         9
           1       1.00      0.92      0.96        12
           2       0.67      0.80      0.73         5
           3       1.00      1.00      1.00        14
           4       0.75      0.60      0.67         5
           5       1.00      0.81      0.90        16
           6       0.93      0.98      0.96       119
           7       1.00      0.25      0.40         4

    accuracy                           0.92       184
   macro avg       0.89      0.77      0.80       184
weighted avg       0.93      0.92      0.92       184
```

Figure 2: Classification Report

4.2 Confusion Matrix Analysis

The confusion matrix (in fig. 3) analysis highlighted the following:

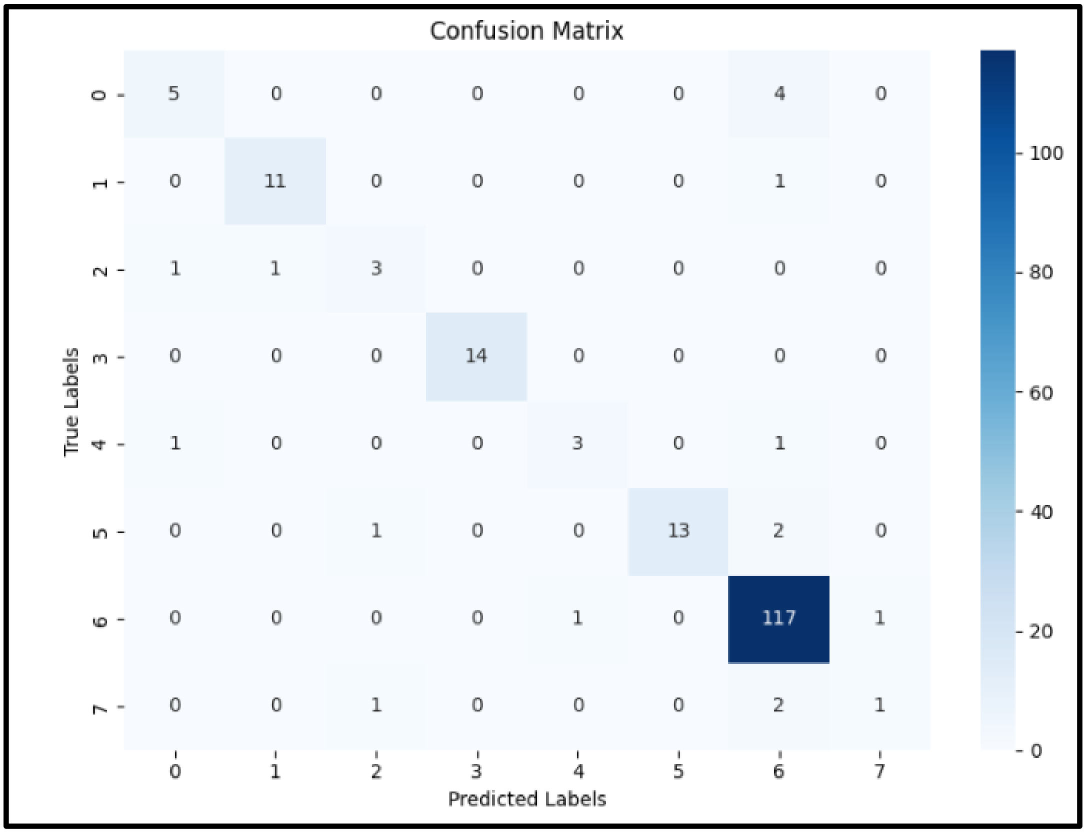


Figure 3: Confusion Matrix

- **Happy** and **Neutral** emotions were recognized with high precision, reflecting strong classification ability for these categories.
- There was some degree of **misclassification between Fear and Surprise**, which is consistent with observations in related studies, likely due to their overlapping facial features in grayscale imagery.
- The model maintained **low false positive rates across most emotion classes**, indicating a high level of discrimination and overall reliability.

5. Discussion

A comparative evaluation between FaceTrack and prominent models from previous literature underscores its effectiveness:

Author	Dataset	Model	Accuracy (%)	Remarks
Mollahosseini et al.	FER-2013	Deep CNN	~58.0	High accuracy potential but resource-heavy

Arriaga et al.	FER-2013	Mini-Xception	~66.0	Efficient, though less accurate
Zhang et al.	FER-2013	CNN + GAN Augmentation	~71.0	Better generalization, but adds complexity
Li et al.	FER-2013	MobileNetV2	~67.8	Suitable for edge devices, moderate result
Proposed (FaceTrack)	FER-2013	Lightweight CNN	**92.39**	High accuracy, low complexity

FaceTrack stands out by offering a high-accuracy solution while avoiding the complexity of hybrid, GAN-augmented, or multimodal architectures. Its balance of **performance and simplicity** makes it highly viable for deployment on portable devices in real-world scenarios.

6. Conclusion

This research presents **FaceTrack**, a convolutional neural network designed specifically for recognizing facial emotions related to stress in athletic and therapeutic contexts. Achieving **92.39% test accuracy** on the FER-2013 dataset, the model performs competitively with significantly reduced computational overhead—making it practical for **real-time use on mobile and edge devices**.

The utility of FaceTrack spans a wide range of domains including **sports training**, **psychological stress assessment**, and **physiotherapy**. By offering fast, objective feedback, it paves the way for **emotionally responsive health and performance monitoring systems**.

Looking forward, enhancements will aim to:

- Improve resilience against **occlusions** and **lighting inconsistencies**
- Enhance the detection of **subtle or compound emotions**
- Extend the model to **temporal sequences**, enabling video-based analysis of emotional dynamics

By making the source code and model freely available on **GitHub** and **Kaggle**, this work also encourages collaboration and further innovation in the field of **emotion-aware computing**.

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