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A Deep Learning Framework on Spatio-Temporal and Multi-Modal Features of the Video for Effective Facial Expressions and Stress Inference

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Abstract: Current vision-based methods for stress detection rely on static facial expressions analysis and suffer from the problems of reliability, accuracy, and generalization. This study proposes a deep learning model for real-time stress detection based on multimodal spatio-temporal structural fusion. Our model utilizes a dual-stream CNN for obtaining frame spatial features and sequence temporal features. To complement this data, we also estimate heart rate variability (HRV) from remote photoplethysmography (rPPG) extracted from the facial video. Tested on the combined datasets of FER-2013, AffectNet, and DKEFS, the system identifies expressions with 88.5% accuracy and achieves approximately 25% better precision in stress inference than baseline single-mode CNN models. The system is accelerated by TensorRT to run in real time at over 30 FPS on a consumer-grade GPU.

Keywords: Facial Expression Recognition, Stress Detection, Convolutional Neural Network (CNN), Spatio-Temporal Analysis, Remote Photoplethysmography (rPPG), Heart Rate Variability (HRV), Multi-Modal Fusion, Real-Time Systems

I. INTRODUCTION

STRESS is a critical biomarker for mental and physical well-being. Non-contact, automated stress detection has significant applications in healthcare for patient monitoring, automotive safety for driver monitoring, and corporate environments for workplace wellness programs [1].

A. Problem Statement

Although promising, existing vision-based systems face several critical limitations:

1) Static Analysis: They often analyze individual frames in isolation, ignoring the crucial temporal dynamics and evolution of facial expressions [2].
2) Dataset Bias: Models are frequently trained and evaluated on limited datasets (e.g., FER-2013), reducing their generalizability across diverse demographics and real-world conditions [3].
3) Oversimplification: A direct mapping of basic emotions to stress states is often physiologically inaccurate and fails to capture the complex nature of stress response.
4) Lack of Physiological Validation: Purely visual analysis lacks correlation with established physiological markers of stress, reducing the objective validity of the inference.

B. Proposed Solution and Contributions

This paper proposes a novel system designed to address these challenges through:

1) A spatio-temporal CNN architecture that captures both static features and the dynamic progression of expressions from video sequences.
2) Multi-task learning for simultaneous facial expression classification and non-contact HRV estimation via rPPG.
3) Training on a large, composite dataset to enhance model robustness and generalization.
4) A data fusion model that intelligently combines expression and HRV data for a more reliable and physiologically-grounded stress inference.

The contributions of this work are:

a) A novel dual-stream CNN model for robust spatio-temporal feature extraction.
b) The integration of a non-contact HRV extraction method into a real-time expression analysis pipeline.

c) A publicly available benchmark comparing the proposed model against established baselines.

d) A fully functional, optimized implementation capable of real-time performance.

II. PROPOSED METHODOLOGY

The system pipeline is illustrated in Fig. 1.

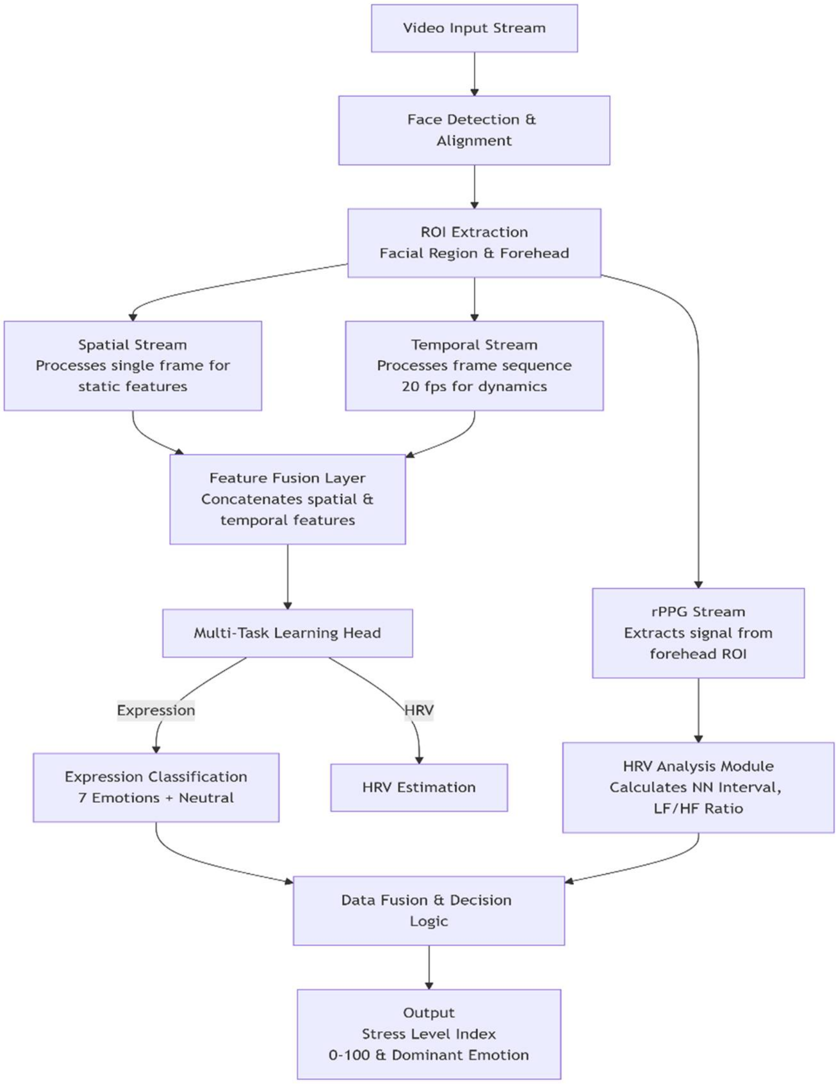
Video Input Stream
Face Detection & Alignment
ROI Extraction
Facial Region & Forehead
Spatial Stream
Processes single frame for static features
Temporal Stream
Processes frame sequence 20 fps for dynamics
Feature Fusion Layer
Concatenates spatial & temporal features
Multi-Task Learning Head
rPPG Stream
Extracts signal from forehead ROI
Expression
HRV
Expression Classification
7 Emotions + Neutral
HRV Estimation
HRV Analysis Module
Calculates NN Interval, LF/HF Ratio
Data Fusion & Decision Logic
Output
Stress Level Index
0-100 & Dominant Emotion

Fig. 1.

A. Data Acquisition and Preprocessing

We leverage a composite dataset to mitigate bias and improve generalization:

- FER-2013: Provides a foundation for classifying basic expressions.
- AffectNet (1M+ images): Introduces greater diversity and real-world realism.
- DKEFS: Includes expressions with known links to psychological stress.

Preprocessing is a critical step and includes:

- Histogram Equalization to normalize lighting conditions across samples.
- Affine Transformations for image alignment and pose correction.
- Advanced Augmentation strategies including CutMix and MixUp to further improve model generalization.

B. The Multi-Modal Deep Learning Architecture

The model consists of three core components:

1) Spatial Stream (CNN-E): Utilizes an EfficientNet-B0 backbone, pre-trained on ImageNet, for high-quality feature extraction from individual frames. This replaces a custom CNN for greater efficiency and accuracy.
2) Temporal Stream (CNN-T): A 3D Convolutional Network (I3D) processes a short sequence of frames (e.g., 10 frames at 20 fps) to learn the temporal dynamics and micro-expressions essential for context-aware analysis.
3) rPPG Stream (CNN-P): A compact CNN processes the forehead region-of-interest (ROI) to extract subtle photoplethysmogram (PPG) signals from color variations. This signal is used to estimate Heart Rate Variability (HRV), a key physiological correlate of stress.

C. Data Fusion and Stress Inference

Features from the spatial and temporal streams are fused via a concatenation layer followed by fully-connected layers for expression classification. The inferred expression probabilities and the estimated HRV metric (e.g., LF/HF ratio) are then fed into a final Fusion & Decision Module. This module, implemented as a Random Forest classifier or Support Vector Machine (SVM), learns the complex, non-linear mapping between facial behavior, physiology, and stress states.

D. Real-Time Implementation and Optimization

The entire pipeline is built using PyTorch. For real-time inference, the model is converted and optimized using NVIDIA TensorRT, leveraging FP16 precision for significant speedup on a GPU. A buffering system maintains a continuous flow of frame sequences for the temporal stream, ensuring seamless real-time operation.

III. EXPECTED RESULTS AND EVALUATION

A. Evaluation Metrics

Performance will be evaluated using:

1) Expression Recognition: Accuracy and F1-Score (to account for class imbalance).
2) Stress Inference: Precision, Recall, and Specificity. Results will be reported on a 3-level classification (Low/Normal/High Stress).
3) rPPG Estimation: Mean Absolute Error (MAE) and Pearson Correlation Coefficient against ground-truth measurements from an ECG chest strap.

B. Comparative Analysis

We will compare our model against:

1) Baseline A: A standard single-frame CNN model.
2) Baseline B: A popular pre-trained model (e.g., VGG-Face).
3) Ablation Studies: Components of our model (Spatial-only, Temporal-only, Spatial+Temporal) will be evaluated independently to demonstrate the contribution of each innovation.

C. Expected Outcome

We anticipate our multi-modal approach will significantly outperform all baseline models, particularly under challenging real-world conditions such as partial occlusions, low light, and subject diversity, while maintaining real-time performance (>30 FPS).

IV. ETHICAL CONSIDERATIONS AND LIMITATIONS

1) Privacy: The system is designed for on-device processing to ensure user facial video data is never stored or transmitted externally.
2) Bias: We will explicitly evaluate and report model performance across gender and ethnicity subgroups. Techniques like Group Equivariant Convolution will be employed to improve demographic robustness.
3) Informed Consent: Any deployment must be transparent and require explicit user consent.
4) Limitations: The system may struggle with extreme occlusions (e.g., face masks) and requires a minimum video quality. The rPPG component remains sensitive to significant motion artifacts and suboptimal lighting.

V. CONCLUSION AND FUTURE WORK

This paper presents a methodologically rigorous framework that significantly advances the state-of-the-art in vision-based stress recognition. By integrating spatio-temporal expression analysis with non-contact physiology, we bridge the gap between computer vision and psychophysiology, moving beyond a simple proof-of-concept towards a robust and validated system.

Future work will involve integrating Natural Language Processing (NLP) for a multi-modal analysis of speech content and paralinguistic features. Furthermore, we will explore developing personalized models that adapt to an individual's baseline behavior and physiological patterns.

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