Real-Time Emotion Recognition System with Emotionalize Score

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Abstract. Emotion recognition systems have achieved high performance in categorical classification. However, they remain limited in capturing the intensity and dynamics of emotional expressions, particularly in real-time scenarios. Subtle facial movements are frequently misclassified, leading to unstable and semantically inconsistent predictions.

We propose Emotionalize, a continuous metric of emotion intensity for real-time emotion recognition. The system combines EfficientNet-B0 for discrete emotion classification with MediaPipe facial landmark extraction to compute geometric features, such as eye openness, mouth opening, and eyebrow contraction.

To ensure temporal stability, the system applies baseline normalization, percentile scaling, and exponential moving-average smoothing, along with a threshold-based event detection mechanism that logs high-intensity emotional episodes.

The proposed system operates in real time at 25–35 frames per second and achieves approximately 93% accuracy on RAVDESS and CREMA-D datasets. The framework provides a practical solution for applications in human-computer interaction, affective computing, and behavioral monitoring, where both emotion type and intensity are critical.

Keywords: Emotion recognition · Facial expression recognition· Real-time inference· Emotion intensity estimation · Human-computer interaction

1 Introduction

Emotion recognition from facial expressions in videos has become an essential problem in human-computer interaction and affective computing (also known as Emotion AI). It is an interdisciplinary field spanning computer science, cognitive science, and psychology. Recent advances in deep learning have significantly improved facial emotion recognition performance by enabling robust classification of expressions into discrete categories such as happiness, sadness, anger, and fear [1, 2]. Despite this progress, most existing approaches remain limited to categorical classification, where each frame is assigned a single predefined emotion label.

Although discrete emotion classification is useful, it often falls short in real-world applications that require a more nuanced understanding of affective states. In many scenarios, the intensity of the expression is as important as the emotion category itself.

To address these limitations, recent research has explored dimensional affective models, intensity-aware recognition approaches [3–5], and facial action coding systems (FACS) [11]. Although these approaches provide richer emotional representations, they often require specialized annotations, additional modalities, or computationally expensive processing pipelines, making them less suitable for lightweight real-time applications.

Motivated by these challenges, we propose a real-time framework for facial emotion analysis that extends categorical emotion recognition with a continuous intensity measure, referred to as the *Emotionalize score*. The proposed framework combines two complementary sources of information. First, a lightweight Convolutional Neural Network classifier (EfficientNet-B0) produces probabilistic estimates over discrete emotion classes. Second, facial landmarks extracted using MediaPipe Face Mesh are used to compute interpretable geometric descriptors, such as eyebrow tension, eye openness, and mouth opening, which characterize local facial dynamics. These components are fused into a unified Emotionalize metric through a weighted formulation, enabling robust estimation of emotional intensity without requiring explicitly labeled intensity data.

The proposed system operates in real time using a standard webcam and achieves stable performance at interactive frame rates, providing both categorical emotion labels and a continuous, interpretable estimate of emotional intensity. This makes it particularly suitable for applications requiring lightweight, vision-only, and temporally stable emotion analysis, such as clinical monitoring, affective computing, and human–robot interaction [1, 2, 13, 14].

2 Previous Work

2.1 Deep Learning for Emotion Recognition

Facial emotion recognition (FER) from images and videos has significantly advanced with the adoption of deep learning methods, particularly convolutional neural networks (CNNs). Recent surveys confirm that CNN-based approaches remain the dominant paradigm [1, 2] due to their ability to learn robust hierarchical representations from facial images. Modern reviews [1, 2] highlight that despite high classification accuracy, FER systems still suffer from sensitivity to environmental variations such as illumination, head pose, and individual facial differences.

Recent architectures prioritize both accuracy and efficiency, especially for real-time applications. Lightweight CNNs, including EfficientNet-based models [8], are widely used due to their favorable trade-off between computational cost and performance. However, most deep learning-based FER systems remain limited to categorical emotion classification, assigning a single discrete label per frame without considering the intensity of the emotional expression.

2.2 Emotion Intensity Estimation

A growing body of recent research has focused on modeling emotion intensity in addition to categorical labels. Multi-task learning approaches, such as MMA-MRNNet [3], jointly predict emotion categories, valence-arousal values, and intensity levels, demonstrating that intensity estimation provides a richer representation of affective states.

Similarly, recent challenges such as the ABAW 2024 competition [4] emphasize the importance of predicting continuous emotional attributes, including intensity, alongside classification [5]. These approaches typically rely on complex architectures combining CNNs with temporal models (e.g., RNNs or attention mechanisms).

2.3 Facial Geometry and Landmark-Based Approaches

In parallel with CNN-based methods, facial landmark analysis has been widely used to capture fine-grained facial dynamics. Recent lightweight frameworks such as MediaPipe Face Mesh [9, 10] enable the real-time extraction of dense facial landmarks with high precision.

Hybrid approaches that combine CNN output with landmark-based features have shown improved robustness compared to models based solely on appearance. Geometric features such as eye openness, mouth opening, and eyebrow contraction provide interpretable signals related to facial muscle activity and can help detect subtle expressions that CNNs alone may misclassify.

Recent studies confirm that integrating geometric features enhances model interpretability and stability, particularly in real-time scenarios [3, 4, 9–12]. However, most existing hybrid methods still focus on improving classification accuracy rather than explicitly modeling emotional intensity.

2.4 Real-Time Emotion Recognition Systems

Real-time FER systems require a balance between accuracy and computational efficiency. Recent works emphasize the growing need for lightweight models capable of operating at interactive frame rates while maintaining robust recognition performance [1,2,12]. However, these systems focus mainly on categorical classification and often lack explicit mechanisms to represent emotional intensity [3–5].

Moreover, recent studies explicitly note that current real-time systems do not adequately capture the strength of emotional expressions, which limits their usefulness in practical applications such as human-computer interaction and behavioral analysis [1–5].

2.5 Summary and Research Gap

The analysis of recent literature reveals several key trends: CNN-based models dominate emotion recognition and achieve high classification accuracy; Emotion intensity modeling is gaining increasing attention in recent studies; Landmark-based methods provide interpretable geometric features; Real-time systems prioritize efficiency, but often lack expressiveness.

There remains a significant gap in existing research. Current approaches typically either focus on classification without emotion intensity measure or model intensity using complex and computationally expensive architectures. There is a lack of methods that simultaneously operate in real time, provide a continuous and interpretable measure of emotional intensity, and remain computationally lightweight.

To address this gap, the present work introduces a hybrid framework that integrates CNN-based emotion probabilities with facial geometry into a unified metric, *Emotionalize*, specifically designed for real-time emotion intensity estimation.

3 Methodology

3.1 Emotion Definition and Psychological Basis

The set of emotion classes used in this work is based on widely accepted psychological models of basic human emotions. In particular, the selected categories (anger, fear, sadness, happiness, surprise, disgust, and neutral) correspond to the fundamental emotions described in the Facial Action Coding System and related psychological studies [11]. According to Ekman's theory, these emotions are universal across cultures and are associated with distinct facial expressions that can be reliably recognized [11]. Each emotion is characterized by specific facial muscle activations, which are reflected in observable geometric changes in the face (see Table 1).

In addition to discrete emotion categories, modern research often considers dimensional models of emotion, such as valence (positive emotion or negative) and arousal (intensity of emotion) [13]. In this framework, emotions are represented along continuous axes, where arousal reflects the intensity of emotional activation. This mapping is based on established findings in affective psychology and facial expression research, including the circumplex model of affect [13], the FACS [11], and contemporary works on multimodal emotion recognition [3, 4]. It represents a consolidated interpretation of valence, arousal, and observable facial characteristics for each emotion class, basic for the real-time recognition system.

From a psychological perspective, high-arousal emotions such as anger, fear, and surprise are associated with increased physiological and facial activation, while low-arousal states such as sadness and neutral expression correspond to reduced activity. This observation directly motivates the weighting scheme used in the emotion energy formulation (see Sections 3.6-3.7), where high-arousal emotions contribute more significantly to the overall intensity score.

Table 1. Psychological interpretation of emotion classes

Emotion	Valence	Arousal	Description
Angry	Negative	High	Associated with tension, aggression, and strong facial muscle activation (e.g., brow contraction) [11].
Fear	Negative	High	Characterized by wide eyes and alertness; reflects threat perception [13].
Sad	Negative	Low	Associated with low energy and reduced facial activity.
Happy	Positive	Medium	Expressed through smiling and relaxed facial features.
Surprise	Neutral	High	Sudden reaction with wide eyes and raised eyebrows.
Disgust	Negative	Medium	Characterized by nose wrinkling and upper lip raising; reflects rejection of aversive stimuli [11].
Neutral	Neutral	Low	Absence of strong emotional activation; baseline facial state.

3.2 Overview of the Proposed Pipeline

Conventional CNN-based emotion recognition systems often produce unstable predictions, particularly for weak or ambiguous facial expressions. In these cases, neutral emotional states (i.e., lacking strong positive or negative affect) are frequently misclassified as negative emotions, and predictions may fluctuate rapidly between classes. The proposed real-time emotion recognition pipeline (shown in Figure 1) integrates several complementary components. Video frames are first captured from a webcam and processed for face detection. Then, detected faces are cropped with padding and resized to a standard resolution. A CNN-based classifier outputs preliminary emotion probabilities, which are temporally smoothed to reduce fluctuations. Then, facial landmarks are extracted using MediaPipe Face Mesh to compute geometric features such as eye openness, mouth opening, and eyebrow tension. These geometric features are combined with the CNN predictions to calculate the Emotionalize score, a continuous metric representing the intensity of expressions. The final system output consists of both the discrete emotion label and the continuous Emotionalize score, with additional calibration and logging for real-time evaluation.

3.3 Initial Emotion Classification

Emotion classification (step 3 in Figure 1) was performed using a convolutional neural network based on the EfficientNet-B0 architecture [8]. The classification head was adapted to output probabilities for the target emotion classes used in this study: angry, fear, sad, happy, surprise, disgust, and neutral. Given an input image, the model outputs a probability distribution over emotion classes:

$$P = [p_{\text{Angry}}, p_{\text{Fear}}, p_{\text{Sad}}, p_{\text{Happy}}, p_{\text{Surprise}}, p_{\text{Disgust}}, p_{\text{Neutral}}].$$

EfficientNet-B0 was chosen due to its favorable trade-off between accuracy and computational efficiency. It employs compound scaling of depth, width, and

Fig. 1. The proposed real-time emotion recognition pipeline. Video frames are processed for face detection to compute the continuous Emotionalize intensity alongside the final emotion label.

resolution, allowing it to achieve high performance with a relatively small number of parameters and reduced inference time. These characteristics make it especially suitable for real-time emotion recognition applications, where both speed and accuracy are critical.

3.4 Stabilized Emotion Prediction

Standard CNN-based models tend to produce unstable predictions in real-time scenarios, particularly for low-intensity or ambiguous expressions [20]. This often results in misclassification of neutral states, rapid switching between negative emotions, and sensitivity to minor facial movements.

To mitigate these issues, the proposed framework applies temporal stabilization techniques that improve prediction consistency and better reflect natural human emotional behavior, where changes are gradual rather than abrupt. Sliding-window smoothing of predictions is applied to stabilize emotion estimates over time. For each frame t, the predicted emotion probabilities p_t are averaged over a window of N recent frames, resulting in $\hat{p}_t = \frac{1}{N}\sum_{i=0}^{N-1} p_{t-i}$.

3.5 Facial Landmark Feature Extraction

Facial landmarks are extracted using MediaPipe Face Mesh [10], providing a dense set of facial points. From these landmarks, the following geometric features are computed:

- *Eye openness:* measured as the normalized distance between upper and lower eyelids relative to the inter-ocular distance (IOD). This measure ranges from 0 (eyes fully closed) to 1 (eyes maximally open).

- *Mouth opening:* defined as the normalized distance between the upper and lower lips, also relative to IOD. It is expressed by values from 0 (mouth closed) to 1 (mouth maximally open).
- *Eyebrow tension:* computed from the distance between inner eyebrow points or deviation from baseline position, normalized by IOD. This yields a ratio ranging from 0 (minimal tension) to 1 (maximum tension).

3.6 Emotion Energy

To bridge categorical predictions and continuous representation, an intermediate variable called *emotion energy* is introduced:

$$E = \alpha_a\, p_{\text{angry}} + \alpha_f\, p_{\text{fear}} + \alpha_{sad}\, p_{\text{sad}} + \alpha_{sur}\, p_{\text{surprise}} + \alpha_h\, p_{\text{happy}} + \alpha_d\, p_{\text{disgust}} - \alpha_n\, p_{\text{neutral}} \tag{1}$$

The emotion energy term can be interpreted as an approximation of the arousal dimension derived from categorical emotion probabilities, bridging discrete emotion recognition with continuous affect representation.

The coefficients used in the formulation of emotion energy are defined based on the psychological concept of emotional arousal [13,14]. In particular, emotions differ in the level of physiological and expressive activation they induce.

3.7 Emotionalize Metric

In addition to discrete emotion classification, a continuous metric called

$$y_i = \alpha_E E_i + \alpha_B B_i + \alpha_I I_i + \alpha_M M_i \tag{2}$$

where E is an Emotion Energy introduced in Equation 1, and B, I, and M are Eyebrow tension, Eye tension, and Mouth opening, respectively, defined in the Section 3.5.

Unlike classification, which determines the type of emotion, the Emotionalize score provides a continuous measure of how strongly the emotion is expressed. The hybrid representation combines semantic information from CNN predictions with geometric features from facial landmarks. The use of weighted geometric features is supported by prior studies demonstrating that facial landmarks and action-related geometric measurements provide informative descriptors for expression intensity estimation in affective computing, pain assessment, and emotion recognition [3–5, 11]. E received the highest weight to preserve semantic alignment with CNN-predicted emotion classes; B received a moderately high weight as eyebrow movement strongly indicates emotional activation; I received a medium weight to reflect alertness and tension; M received the lowest weight due to its susceptibility to non-emotional variations such as speech (see sections 6.1 and 6.2).

3.8 Emotion Energy and Emotionalize Metrics Callibration

A small-scale subjective calibration experiment was conducted with 10 volunteers (6 males, 4 females; aged 21–34, mean 27.3, std 3.9) to determine the coefficients of the Emotion Energy and Emotionalize metrics. Participants displayed seven emotions (happiness, anger, fear, sadness, disgust, neutral and surprise) at four intensity levels (weak, moderate, strong, very strong) and provided self-reported intensity ratings on a 0–100 scale, yielding 240 samples.

For each sample, CNN-predicted emotion probabilities, geometric facial features (eyebrow tension, eye activation, mouth opening), Emotion Energy, and Emotionalize scores were computed. The relationship between self-reported intensity and Emotionalize was evaluated using Pearson ($r = 0.768$) and Spearman ($\rho = 0.773$) correlations, demonstrating that higher self-reported intensity corresponded to higher Emotionalize values. Prediction error was quantified via MAE (15.5) and RMSE (20.2), showing that while the metric does not exactly reproduce subjective ratings, it reliably captures relative changes in facial activation.

The dataset was then used to estimate regression coefficients for Emotion Energy and Emotionalize through constrained ridge regression. The regression-derived coefficients were normalized and rounded to obtain the final values used in the system.

3.9 Event Detection

An event detection mechanism is used to identify periods of high emotional intensity. An event is defined by the following threshold conditions:

$$\text{start: Emotionalize} \geq T_{\text{start}}, \text{end: Emotionalize} < T_{\text{end}}. \tag{3}$$

For each event, the system records the start and end times, duration, peak intensity, and dominant emotion.

The start and end thresholds were empirically selected based on validation-set analysis to balance responsiveness to genuine emotional peaks with robustness against short-term spurious fluctuations, ensuring stable real-time performance. An emotional event is considered to have started when the Emotionalize score exceeds 90.0 and is deemed to have ended once the score falls below 85.0. In addition, a minimum event duration of 0.7 seconds is enforced, such that events shorter than this duration are ignored in order to prevent false positives caused by transient fluctuations. Macroexpressions are defined by voluntary movements and are characterized by high-intensity movements lasting from 0.5 seconds [21].

4 Dataset

The model was trained and evaluated using two publicly available datasets: CREMA-D [6] and RAVDESS [7]. CREMA-D contains 7,442 video clips in FLV format from 91 actors expressing basic emotions. RAVDESS is an audio-visual

Fig. 2. Sample images from the seven emotion classes (top: Angry, Disgust, Fear, Happy; bottom: Neutral, Sad, and Surprise), with CREMA-D samples shown on a green background and RAVDESS samples on a white background.

dataset containing recordings with variations in emotional intensity in MP4 format. Table 2 presents the descriptive statistics for each dataset, and Fig. 2 illustrates several representative samples. Average duration of each video clip: ∼3.5 seconds for CREMA-D, and ∼4.0 seconds for RAVDESS. Video sequences were converted into individual frames, followed by face detection and cropping. The resulting dataset consisted of 200,167 labeled facial images, from which 98,162 samples belong to the CREMA-D dataset, and 102,005 samples to the RAVDESS dataset.

Following preprocessing and label harmonization (with the *Calm* class merged into *Neutral*), the combined CREMA-D and RAVDESS dataset was divided into training, validation, and test subsets in a 70% / 15% / 15% ratio, while preserving class distribution across all subsets (see Table 3). To avoid data leakage, the split was performed in a subject-independent manner, ensuring that individuals appearing in the training set were not present in the validation or test sets.

5 Experimental Setup

The system was implemented using PyTorch for neural network inference, OpenCV for video processing, and MediaPipe for face detection and landmarks.

5.1 Data Preprocessing

The preprocessing pipeline began with extracting frames from the input video sequences. Faces were detected using MediaPipe and subsequently cropped with a 15% padding applied to the bounding box dimensions to ensure the face is fully captured and context around the face is preserved. The padded regions were resized to 224×224 pixels and normalized using ImageNet statistics (mean: [0.485, 0.456, 0.406], standard deviation: [0.229, 0.224, 0.225]).

Table 2. Dataset statistics for each emotion class in CREMA-D and RAVDESS

Dataset	Angry	Disgust	Fear	Happy	Neutral	Sad	Surprise	Calm
CREMA-D	1271	1271	1271	1273	1087	1271	–	–
RAVDESS	752	384	752	752	376	752	384	752

5.2 Class Imbalance Correction and Calm Merging

After analyzing the distribution of emotion classes (Table 2), it was observed that certain emotions, such as *Surprise* and *Disgust* (RAVDESS), were underrepresented compared to *Angry*, *Happy*, and *Sad*. To reduce potential bias towards frequent classes, the following strategies were applied. Additionally, the *Calm* class in RAVDESS was merged into the *Neutral* category during preprocessing to simplify the classification task and improve model stability.

1. Oversampling of minority classes: Videos corresponding to underrepresented emotions (*Surprise* and *Disgust* in RAVDESS) were oversampled in the training set to balance class frequency within each batch.
2. Data augmentation: In addition to duplication, standard data augmentation techniques were applied, including horizontal flipping, brightness and contrast adjustments, and minor affine transformations. These augmentations increase variability and improve the model's generalization to variations in facial appearance, lighting, and minor pose differences.
3. Class weighting: The weighted cross-entropy loss was used to mitigate class imbalance:

$$\mathcal{L} = -\sum_{i=1}^{K} w_i \, y_i \log(\hat{y}_i), \tag{4}$$

where y_i is the ground-truth label, $\hat{y}_i$ is the predicted probability for class i, and w_i is the class weight defined as

$$w_i = \frac{N_{\text{total}}}{K \cdot N_i}, \tag{5}$$

where N_i denotes the number of training samples in class i, N_{total} is the total number of training samples, and K is the number of emotion classes.

6 Results

The experiments were performed on a workstation equipped with an NVIDIA RTX 2060 graphics processing unit and an AMD Ryzen 7 4800H central processing unit. The system operates in real time at approximately 25–35 frames per second (FPS). The experimental evaluation of the proposed system was conducted in two stages: (1) offline evaluation of the emotion classification model, and (2) real-time testing of the full system.

Table 3. Dataset split used for model training and evaluation

Dataset	Train (70%)	Validation (15%)	Test (15%)
CREMA-D	68,713	14,724	14,725
RAVDESS	71,404	15,301	15,300
Total	140,117	30,025	30,025

6.1 Emotion Energy Coefficient Estimation

The coefficients in Eq. 1 were experimentally determined through iterative testing on the training datasets. Several configurations were tested with coefficient values ranging approximately from 0.05 to 0.35 for positive emotion weights and from -0.15 to 0 for negative adjustments (in 0.05 increments).

The coefficients for Emotion Energy were estimated using constrained ridge regression:

$$y_i = w_a p_{angry} + w_f p_{fear} + w_{sad} p_{sad} + w_{sur} p_{surprise} + w_h p_{happy} + w_d p_{disgust} + w_n p_{neutral} \tag{6}$$

with constraints to ensure high-arousal emotions had larger positive weights and neutral expressions had non-positive contribution.

The coefficients reported in Table 4 and 5 were obtained through a three-stage calibration procedure. First, a constrained ridge regression model was fitted using participant self-reported intensity as the target variable and CNN emotion probabilities as predictor variables. This procedure produced the raw regression coefficients shown in the second column of the table.

To make the coefficients comparable and preserve their relative contributions, the raw coefficients were normalized as follows:

$$w_k^{\text{norm}} = \frac{w_k}{\sum_{i=1}^{K} |w_i|} \tag{7}$$

where w_k denotes the raw regression coefficient and K is the number of emotion classes. Normalization by the sum of absolute coefficient values preserves the relative importance of each emotion while keeping the overall scale consistent. The final coefficients are rounded to two decimal places for interpretability and stability, while preserving the arousal ordering consistent with psychological literature.

6.2 Emotionalize Fusion Weights Estimation

After computing Emotion Energy, a second constrained ridge regression was performed to combine semantic and geometric features: *Emotionalize* is introduced to estimate the intensity of facial expressions:

$$\text{Emotionalize} = 0.45E + 0.20B + 0.15I + 0.10M, \tag{8}$$

with constraints $\alpha_E > \alpha_B > \alpha_I > \alpha_M \geq 0$ to reflect the dominance of Emotion Energy over geometric features. In the Table 4 and Table 5 we describe coefficients for metrics Emotionalize (4) and Emotion Energy (5).

6.3 Emotion Classification Stability

To evaluate the stability of our proposed model, we compared it against two baseline architectures: (1) a standard CNN model trained on FER2013 following

Table 4. Emotion Energy Coefficients (Eq. 1)

Emotion	Raw	Normalized	Final
Angry	0.314	0.283	0.28
Fear	0.271	0.244	0.24
Surprise	0.182	0.164	0.16
Sad	0.151	0.136	0.14
Happy	0.109	0.098	0.10
Neutral	-0.118	-0.106	-0.10
Disgust	0.225	0.203	0.20

Table 5. Emotionalize Coefficients (Eq. 7)

Feature	Raw	Normalized	Final
Emotion Energy (E)	0.493	0.468	0.45
Brow tension (B)	0.223	0.212	0.20
Eye activation (I)	0.158	0.151	0.15
Mouth opening (M)	0.126	0.120	0.10

the architecture of Khaireddin & Chen [17], and (2) a CNN-LSTM model evaluated on the CREMA-D dataset [16]. All models were evaluated on our validation set under identical conditions.

Neutral state preservation. The baseline CNN misclassified neutral expressions as negative emotions in 27% of frames (accuracy 73%), while the CNN-LSTM baseline achieved 79% neutral frame accuracy. In contrast, our proposed model correctly identified neutral expressions in 88–90% of frames, representing a relative improvement of 11–17% over the best baseline.

Temporal consistency. Abrupt label changes between consecutive frames were reduced by approximately 70% using sliding-window smoothing with majority voting, compared to the raw CNN predictions and prior work [3, 12].

6.4 Emotion Event Detection

The event detection mechanism identified periods of high emotional intensity (Emotionalize score exceeds 90). For each detected event, the system accurately recorded the start and end timestamps, duration, peak intensity, dominant emotion.

6.5 Quantitative Comparison with Existing Methods

The proposed approach achieves competitive performance compared to existing emotion recognition methods (Table 6). While some state-of-the-art systems report higher absolute accuracy, the proposed model offers several practical advantages that make it particularly suitable for real-world, real-time applications.

As shown in Table 7, our model achieves 93% accuracy while requiring only 5.3M parameters and 12 ms inference time per frame. In comparison, the DCRF-based multimodal model [15] achieves 93.7% accuracy but uses 32.1M parameters (6× larger) and 35 ms inference time (∼3× slower), and requires both audio and video inputs.

Overall, the proposed approach provides a favorable trade-off between accuracy (93%), computational efficiency (5.3M parameters, 12 ms/frame), and temporal robustness, making it suitable for real-time emotion recognition in uncontrolled environments.

Table 6. Comparison of the proposed model with recent emotion recognition approaches

Method / Dataset	Accuracy (%)	Notes
Proposed model (CREMA-D + RAVDESS) [6, 7]	93	Real-time video-only processing with temporal smoothing
DCRF-based multimodal model (RAVDESS, TESS, SAVEE, EmoDB, Crema-D) [15]	93.7	Audio-visual hybrid model with deep recurrent architecture
CNN-LSTM (CREMA-D) [16]	79	Single-modality video-based emotion recognition
CNN (FER2013) [17]	73	Static image-based emotion classification benchmark (video not used)
Modern CNN (CK+, curated datasets) [19]	95–99	Controlled conditions with high-quality labeled images, single-modality (video)

7 Discussion

The primary contribution of this work lies in improving the stability of emotion classification. Unlike standard approaches that rely solely on frame-level predictions, the proposed method incorporates temporal smoothing and post-processing, resulting in significantly more consistent outputs. This is especially important in cases of weak or ambiguous facial expressions, where traditional models tend to produce unstable or misleading predictions.

The introduction of the Emotionalize metric provides an additional layer of analysis by capturing the intensity of facial expressions. While not intended to replace categorical classification, this metric enhances interpretability and allows for a more nuanced understanding of emotional dynamics. The use of geometric facial features ensures that the intensity measure remains interpretable and directly linked to observable facial movements.

Table 7. Comparison of model complexity and efficiency

Method	Modalities	Parameters (M)	Inference time per frame (ms)	Notes
Proposed framework (CREMA-D&RAVDESS)	Video only	5.3	12	Lightweight, real-time
DCRF-based multimodal model [15]	Audio + Video	32.1	35	Multimodal, larger model
CNN-LSTM (CREMA-D) [16]	Video only	12.4	28	Standard CNN-LSTM architecture
CNN (FER2013) [17]	Video frames / images	6.0	15	Static image-based baseline
Modern CNN (CK+, curated) [19]	Video / images	20–25	30	High-quality images, larger network

The experimental results demonstrate that the proposed system achieves high emotion classification accuracy (93%) while maintaining stable real-time performance under continuous video input. In addition to accurate recognition, the framework significantly improves temporal consistency of emotion predictions, reducing abrupt frame-to-frame fluctuations commonly observed in conventional CNN-based approaches. The introduction of the interpretable *Emotionalize* metric further enhances the system by providing a continuous measure of facial emotional activation rather than relying solely on discrete emotion labels.

8 Conclusions

In this work, a real-time emotion recognition system was presented, focusing on improving the stability and reliability of emotion classification. The proposed approach combines CNN-based emotion recognition with temporal stabilization and facial geometry analysis, resulting in more consistent and realistic predictions compared to conventional methods.

In addition, a supplementary metric, Emotionalize, was introduced to estimate the intensity of facial expressions. This metric provides a continuous and interpretable representation of emotional dynamics and complements categorical emotion recognition.

Future work will focus on learning optimal Emotionalize weights through data-driven approaches, incorporating temporal deep learning models such as long short-term memory networks and transformer architectures, extending the framework to support multimodal emotion recognition, and improving robustness under challenging real-world conditions.

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