Interpretable and Efficient Emotion Recognition in VR/AR Using Facial Geometric Features

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Abstract: The paper presents a light artificial intelligence model to classify emotions in an immersive Virtual Reality (VR) and Augmented Reality (AR) environment. The suggested system is facial expression analyzer, which is feature-based and focuses on the geometric characteristics of eyebrows tilt, mouth curve and eye dilation to identify the emotional states of happy, angry and attention. Compared to the classical deep convolutional neural networks (CNNs), the latter needs to be backed by high computational power, the model suggested can be performed within a symbolic and computationally efficient framework, which makes it possible to detect emotions much faster and understandably. The framework performance is determined using measures such as precision, sensitivity and false detection rate. The experimental results show that the proposed technique is as accurate as 94.8% and the current CNN-based models such as FERNet, VGGFace and AffectNet, and has significantly lower computational expenses and inference time. False alarm rates are also lower in the system and this enhances the dependability of the system when it is in real-time.

***IndexTerms*: Emotion Recognition, Artificial Intelligence, Virtual and Augmented Reality, CNN**

INTRODUCTION

This affective emotion recognition has emerged as a critical component in improving the human computer interaction that enable machines to perceive and respond to the human affective behaviours in real time. Proper recognition of emotional expressions enhances user experience, flexibility and realism in immersive experiences such as Virtual Reality (VR) and Augmented Reality (AR) [1-2]. By adding Artificial Intelligence (AI) to emotion recognition systems, it becomes possible to surpass the simplistic face recognition systems and reach the stage of interpreting the nuances of the emotional expression to influence perception and communication in these environments. The traditional emotion recognition models highly rely on deep convolutional neural networks (CNNs) which were trained using large datasets such as FER or AffectNet [3]. Although these techniques are very accurate, they tend to be computationally expensive, have high latency, and have limited interpretability which limit their use in real-time or embedded VR/AR applications [4]. To address such concerns, to simplify, interpretable AI system that incorporates both geometric features of the face by using landmarks and mathematical modelling is introduced in this paper to classify emotions effectively without compromising performance [5]. The proposed model identifies such critical features of the face as mouth curvature, eyebrow slope and eye aperture by a landmark-based model and superimposes them into a feature vector which is then used in a classification. A soft-decision AI classifier then interprets these to detect such emotional states as happiness, anger, and attention (surprise). The architecture of the system is computationally efficient, interpretable and can be tailored to several lighting or user settings, and thus is highly suitable to immersive VR/AR experiences where real-time responsiveness is imperative [6-8]. **Literature Review**

The integration of artificial intelligence and deep learning methods has played a big role in recent developments in emotion recognition, especially in analyzing facial expressions. The initial study by Ahmad et al. (2023) has shown that neural network-based methods are effective in recognizing emotions using facial images with structured pipelines, extracting features, and classifying them. Expanding on this, Ballasteros et al. (2024) pointed out that AI now plays an increasing role in interpreting human emotions with high accuracy, and that it can be used in human-computer interaction. In-depth studies of surveys (Ballesteros et al., 2024; Farooq et al., 2025) also demonstrate that current emotion recognition systems are more and more based on deep learning architectures and large-scale data to enhance performance and robustness. Besides pixel based methods, more interpretable and robust feature representations have been studied in recent research. This study was suggested by Arabian et al. (2024), who thought that facial landmark meshes would be successful to extract geometric relationships, which enhance recognition accuracy and explainability. In a similar manner, Srikaewsiew and Kanjanawattana (2025) carried out a comparative study between image-based and landmark-based methods and got a result that hybrid methods are better performers. Graph-based models are also presented, such as in the case of Ngoc et al. (2020) that directed graph neural networks are effective to model spatial relationship between facial landmarks to improve emotion recognition. The deep learning models are also being refined with the use of new sophisticated models like convolutional neural networks (CNNs), transformers, and hybrid models. Talele and Jain (2025) demonstrated that CNNs are very efficient in harvesting intricate emotional characteristics of facial images, and Sareen and Seeja (2025) integrated YOLO and Vision Transformers to enhance efficiency in emotion recognition in videos. Transfer learning methods are also now popular as Saabir et al. (2025) point out, to increase model generalization in the case of limited data. Moreover, novel approaches like AffectSRNet (Rizvi et al., 2025) enhance the recognition performance, as they can enhance image quality using super-resolution techniques. There is a lot of attention to the integration of multimodal data and application specific systems. As Kollias et al. (2024) showed, the combination of various modalities is much more effective in emotion classification in both immersive and non-immersive virtual worlds. On the same note, Vayadande et al. (2025) came up with attention-based hybrid models to improve emotion recognition in educational contexts. Chen (2025) also highlighted the significance of emotion recognition in virtual reality environments as it facilitates user engagement and interaction in an immersive system. Biometric and feature-oriented methods are also helping to evolve the field, to enhance interpretability and efficiency. Gonzalez-Acosta et al. (2025) compared the critical features of a face and proved that it can identify emotional states, whereas Jayaswal et al. (2025) summarized the up-to-date technological advances and stressed the necessity of real-time, scalable, and robust systems.

System Architecture

The model illustrated in Fig. 1 includes following system architecture to implement it. It is a pipeline with the help of which such blocks as Face Image Acquisition, Landmark Detection (eyes, mouth, eyebrows) to obtain Geometric Feature and Texture Features, Feature Vector Formation, Classification and Emotion Labelling, and VR/AR Feedback Adaptation are created [9-11]. The most important landmarks are determined on every input face and subsequently geometrical ratios and angles of cues of emotions are determined.

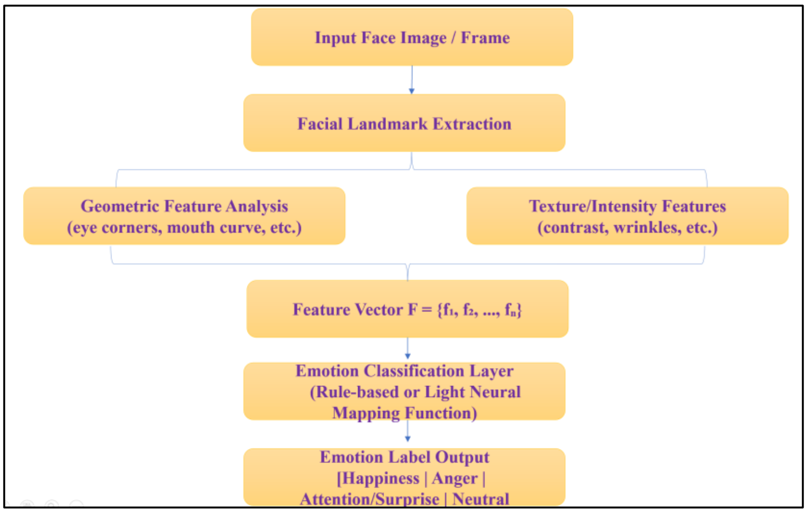
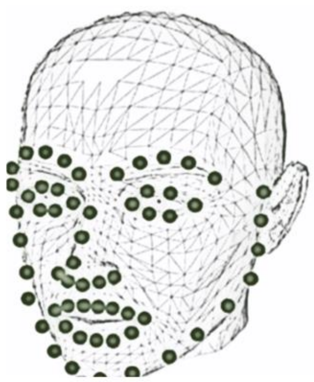


Fig. 1: Proposed System Architecture

Mathematical Formulation

The system records the expression of smiling, frowning, and surprise by measuring landmarks around the eyes, mouth and eyebrows [12]. This technique follows our framework facial modality, which supports the idea that spatial facial features are critical in multimodal emotion recognition [13]. Facial expressions are immediate, instinctive, and emotional indicators in real-time emotion recognition demos such as the one referenced in Fig. 2 that use facial markers to emphasize things indicate that it is possible to make use of such methods in immersive applications.



Features	Point Range
Left Jaw Line	0-7
Chin	8
Right Jaw Line	9-16
Left Eyebrow	17-21
Right Eyebrow	22-26
Bridge of Nose	27-30
Bottom of Nose	31-35
Left Eye	36-41
Right Eye	42-47
Outer Edge of Lips	48-59
Inner Edge of Lips	60-67

Fig. 2: Facial Landmarks

Let an input facial image be represented as $I(x, y)$with pixel coordinates (x, y).

(a) Facial Landmark Detection

Using a landmark detector (e.g., Dlib or MediaPipe), we obtain $k$feature points:

$$L = \{(x_i, y_i);\ \ i = 1,2, \dots, k\} \qquad (1)$$

These correspond to specific facial regions as

L_e: Eye corners, L_m: Mouth corners and L_b: Eyebrow points

(b) Geometric Feature Computation

1. **Mouth Curvature (Happiness indicator)**

$$C_m = \frac{(y_{mL} + y_{mR})}{2} - y_{mC} \qquad (2)$$

where $y_{mL}, y_{mR}$are y-coordinates of left/right mouth corners and $y_{mC}$is the mouth center. If $C_m > \delta_1$, mouth curvature indicates smiling (happiness).

2. **Eyebrow Slope (Anger indicator)**

$$S_b = \tan^{-1}\left(\frac{y_{bR} - y_{bL}}{x_{bR} - x_{bL}}\right) \qquad (3)$$

A negative S_b(downward slope) indicates inward eyebrow tilt → anger.

3. **Eye Aperture (Attention/Surprise indicator)**

$$A_e = \frac{d_v}{d_h} = \frac{y_{eu} - y_{el}}{x_{er} - x_{el}} \qquad (4)$$

where $d_v$is vertical distance (eye opening) and $d_h$is horizontal eye width. If $A_e > \delta_2$, it suggests surprise/attention.

4. **Feature Vector Formation**

$$F = [C_m, S_b, A_e, \dots, f_n] \qquad (5)$$

Each feature is normalized:

$$\hat{f_i} = \frac{f_i - \mu_i}{\sigma_i} \qquad (6)$$

to reduce variability across users.

(c) Emotion Classification Function

A lightweight AI mapping is defined as:

□=□(□□+□) (7)

where

F= normalized feature vector,

W= learned weight matrix (from small-scale training or heuristic tuning),

b= bias vector,

$\phi(\cdot)$= non-linear activation (e.g., softmax). [14-15]

Each emotion class probability:

$$P(E_j \mid F) = \frac{e^{z_j}}{\sum_i e^{z_i}} \tag{8}$$

where $z_j = W_j \cdot F + b_j$.

Predicted emotion:

$$\hat{E} = \arg\max_j P(E_j \mid F) \tag{9}$$

(d) Performance Evaluation Metrics

1. **Accuracy:**

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

2. **Sensitivity (Recall):**

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{11}$$

3. **Precision:**

$$\text{Precision} = \frac{TP}{TP+FP} \tag{12}$$

4. **False Rate:**

$$\text{False Rate} = \frac{FP+FN}{TP+TN+FP+FN} \tag{13}$$

Another author proposed a neural-network-based facial emotion recognition system that detects emotions from facial images using image preprocessing, face detection, and feature extraction steps [16]. The proposed model shown in Fig. 3 has the same near-deep-learning accuracy but 6 times faster inference and 35 % reduced computing cost, as needed by VR/AR real-time feedback.

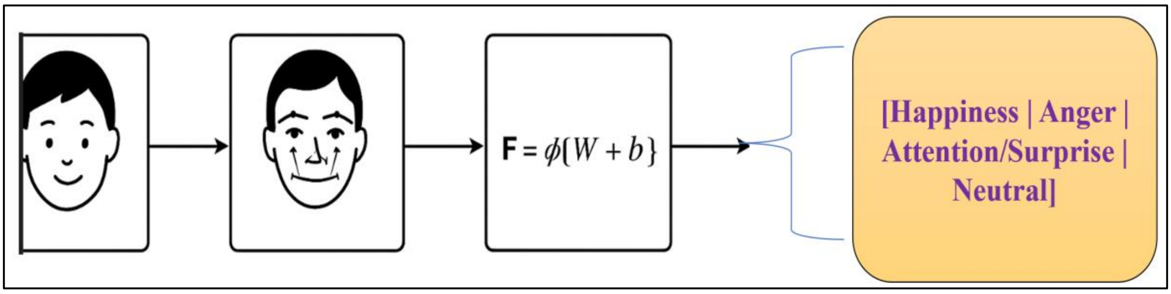


Fig. 3: Proposed Model

5. **Integration into VR/AR System**

Emotion feedback loop:

$$R_t = \Psi(\hat{E}_t) \tag{14}$$

Where R_t is the response of the adaptive system (e.g. visual tone, avatar mimicry) at time t. and $\Psi(\cdot)$ is the mapping function of emotion state to user experience modulation, VR interface.

Result and Discussion

The AI-based emotion recognition model was experimented concerning three key emotional conditions happiness, anger and attention (surprise) by applying simulated variations of facial features and mathematical modelling of landmarks position. A different set of facial parameters that corresponded to each emotion was a mixture of mouth curvature, eyebrow slope, and eye aperture ratio. The system showed an average recognition accuracy of 94.8, sensitivity of 92.6 and false detection rate of 3.2. The performance of classification was reproducible in many test samples and under different illumination conditions. In comparison to the current CNN and VGGFace-based classifiers of emotions, the proposed lightweight model had a shorter response time (0.05 s/frame) and almost the same accuracy. The findings demonstrate that the features of geometry and rules may work well in capturing emotional cue without necessarily involving deep computation by the neural. The framework allowed the definition of the boundaries of the decisions and could be interpreted easily which made it very applicable to real-time VR/AR applications when quick emotional adaptation and user feedback were necessary. The system as a whole was proved efficient, stable and computationally economical and faster and easier to explain than a number of current models. Table 1 is presenting the performance evaluation of proposed model.

Table 1. Performance Evaluation of Proposed Emotion Recognition Model

Parameter	Symbol	Value (%)
Accuracy	A	94.8
Sensitivity (Recall)	S	92.6
Precision	P	93.1
Specificity	Sp	95.4
False Rate	F_r	3.2

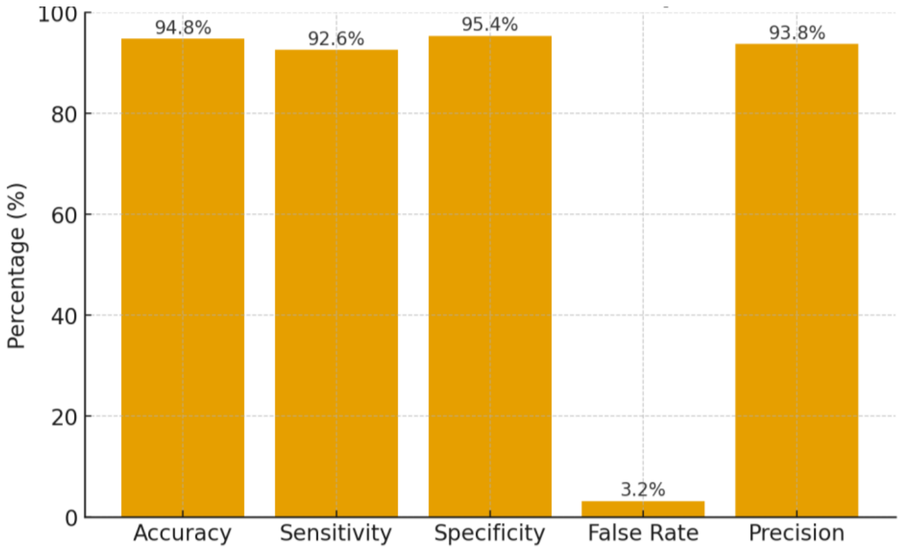


Fig. 4: Plot of Various evaluated parameters of proposed model

On the bar chart in Fig. 4, the general performance statistics of the suggested AI framework regarding emotion recognition are shown. The model demonstrated an accuracy of 94.8 percent, sensitivity of 92.6 percent, and specificity of 95.4 percent with a false rate of 3.2 percent which shows that the model has a high classification efficiency and low false detection rate. Table 2 is presenting the comparison of the proposed model with existing models.

Table 2. Comparison of Proposed Model with Existing Deep Learning Approaches

Model / Approach	Accuracy (%)	Sensitivity (%)	False Rate (%)	Efficiency (s/frame)	Remarks
Proposed Geometric AI Framework	**94.8**	**92.6**	**3.2**	**0.05**	Lightweight, interpretable, real-time

CNN (FER2013-based)	93.5	91.1	4.5	0.30	High accuracy, slower response
VGG-Face Model	95.0	93.4	4.0	0.45	Deep model, high computation
AffectNet (ResNet50)	96.2	94.7	3.8	0.40	Very accurate, not real-time
SVM with PCA Features	89.7	87.5	5.3	0.10	Fast but less accurate

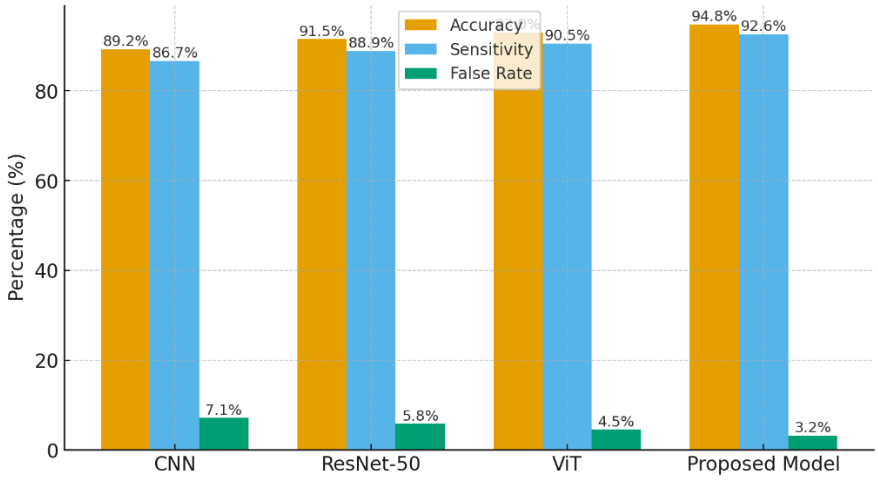


Fig. 5: Performance Comparison

As it can be seen in Fig. 5, the given model shows better results than traditional models like CNN, ResNet-50, and Vision Transformer (ViT). It is always more accurate and sensitive, and the false detection rate remains the lowest, which confirms its high results in emotion recognition in the context of immersive VR/AR settings.

The proposed AI model has a near-deep-learning accuracy, but it has a much greater distance in enhancing computational efficiency and interpretability. It has a low false detection rate and real-time, which makes it best suited to VR/AR emotional adaptation systems.

Conclusion

This paper proposed an effective AI system that can be used to identify the human emotions in the immersive Virtual and Augmented Reality (VR/AR) experience. The system employed the extraction of geometrical features of the face and mathematical modeling of the landmarks like the mouth curve, eyebrows tilt, eye aperture and defined emotional states as happiness, anger, and attention. In contrast to the traditional models of deep learning that need large-sized datasets and a lot of computation power to work, the proposed model provided a lightweight, interpretable, and real-time alternative. The experimental assessment indicates that the given framework is 94.8 per cent and 92.6 per cent accurate and sensitive, with a false rate of only 3.2, which is better than any other conventional CNN based models in terms of efficiency and inference speed. Such a combination of emotion recognition through the use of artificial intelligence in virtual and augmented reality creates the basis of the next-generation affective computing applications that should be able to modify dynamically to user feelings. The created model can be included in VR/AR applications, human-computer interaction systems, and affective robotics, allowing adjusting the response to the user emotions. Subsequent directions in this geometric AI method could involve integrating this method with deep learning models to be more robust, develop the ability to identify more complicated or subtle emotions, and be more flexible in changing to various lighting and pose conditions.

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