Lightweight CNN-Based Real-Time Emotion Recognition for Human Computer Interaction Enhancement

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Abstract: Facial expression recognition is essential in achieving natural interactions between human and machine. In this study, we present an efficient CNN framework for real-time facial emotion recognition in human-computer interaction (HCI) systems. In contrast with classical models which are affected by a high latency when dealing with real sequences, ad-hoc CNN architecture has been incorporated, which has low computational load, hence an efficient and accurate emotion classification that can be achieved in dynamic and low-resource conditions. The framework is tested on variety of datasets and real time video sequences to showcase its strength to occlusions, variation in light, and gradual emotional change. Experimental results demonstrate that the system is promising for practical haptic applications in HCI systems, e.g., virtual assistant, smart classroom, or interactive kiosk.

1 INTRODUCTION

Human-computer interaction (HCI) is now in transition to a new era, where more emotionally intelligent systems that can interpret and respond to human affective states are becoming a reality. It is generally believed that of all sensory recognition modalities for emotions, facial expressions are the most natural, non-verbal, and universally recognized channel. “Incorporating facial emotion recognition into HCI will help the machine become more customized, handle users interactively, and make more human-friendly experiences in education, healthcare, customer services, and entertainment,” said Hui Yu.

Deep learning such as convolutional neural networks (CNNs) has significantly promoted the performance of facial emotion recognition systems to learn deep features directly from raw images. All these previous models are computationally demanding, which implies being unfeasible for real-time applications where latency, hardware restriction and processing speed are vitally importance. Systems applied in realistic settings have to deal with dynamic conditions such as Illumination, occlusion, pose and spontaneous emotions expressions, which can hinder recognition performance and affect user experience.

In the wake of these challenges, we propose a lightweight CNN model that is designed specifically for real-time facial emotion recognition in HCI applications in this research. The model is constructed so as to have lightweight characteristics to run on resource-limited devices but with the accuracy preserved, thus being made suitable for real-time applications, such as smart kiosks, virtual classrooms, mobile apps, and assistive devices. By efficiently designing the network depth, kernel operation, and leveraging effective pre-processing

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techniques, we can reduce the inference time and keep the stability in case of various environments.

In addition, cross-dataset validation and live video testing is involved to guarantee the generalization and possibility of real-world applications of the system. Contrary to base models that are learned based on static datasets this framework focuses on dynamic streaming input data to represent situation of true interaction. The outcome is an emotion recognition system with high reaction to individual emotions, contributing positively to a powerful human-computer partnership, introducing more empathy and greater intelligence into interactive systems that are intelligent.

2 PROBLEM STATEMENT

With the recent trend of technology pervading everyday lifestyle of human beings, the demand for urbane emotional aware computers who can comprehend and demonstrate feedback to the user emotions is ever growing. Facial expression recognition is one of the most important process in assisting people with providing human-computer interaction which can makes computer to understand and respond appropriately to subtle non-verbal cues. However, current models applied to facial emotion recognition are often quite limited for real-time HCI. The vast majority of CNN-based methods emphasize accuracy rather than computational efficiency. These models usually need high-performance devices, a big amount of memory, and long processing times, which make them unfeasible for real-time applications in constrained devices like mobile devices and embedded systems.

Furthermore, most current systems are developed using controlled, static image datasets, which do not reflect the the dynamic environment and conditions in practice. With presence of facial occlusions in-the-wild, lighting variations, pose changes and spontaneous expressions, the dependability of these models is further challenged. Therefore, these works have poor performance for real-time systems with immediate and adaptive response requirement.

To this end, the work at hand attempts to curb such challenges by designing a lightweight and effective CNN-based model that can be used for the real-time facial emotion detection. The main requirement is to achieve accurate recognition results with least computational burden, therefore the system becomes more applicable to wide range of HCI applications. Grounded in emotional intelligence, and aiming to blur the lines between performance and responsiveness, this work strives to develop next-generation interactive systems.

3 LITERATURE SURVEY

Facial emotion recognition (FER) has been increasingly recognized as vital in the development of intelligent systems, particularly in the space of human computer interaction (HCI). Deep learning Most notably CNN, which has driven the transition from manually designed feature extraction to automatic, hierarchical learning from face images. Agung et al. (2024) used CNNs on the Emognition dataset to improve image-based FER and emphasized difficulties for real-time usage. Bagane et al. (2022) introduced a CNN based model for FER but is used for static images and not for dynamic environments as we are.

To overcome the limitation in model depth and prediction accuracy, Boudouri and Bohi (2025) proposed EmoNeXt, a state-of-the-art FER model based on ConvNeXt structure that showed very good accuracy while requiring more computation. Patel and Desai (2022) proposed compact four-layer ConvNet for emotion classification to reduce training time, but it requires better generalization. Savchenko (2021) utilized multi-task lightweight networks that balance speed and accuracy for expression and attribute recognition.

Temporal context has been incorporated by employing hybrid models such as CNN-LSTM, for example Mishra and Sharma (2023) used Chebyshev moments for better sequence modeling. This was further developed by Qin and Wang (2022) in the context of a two-layer attention mechanism. Singh and Kumar (2022), used optimized CNNs for real-time performance and showed that it reduced the latency in various environments.

The problem of cross-dataset generalization is still an open issue. Gao and Wang (2022) concatenated CNN and Central Local Binary Pattern (CLBP), while Saini and Singh (2021) proposed EmNet, which was trained on the in-the-wild data to be robust. Yadav and Raj (2023) and Nair and Gupta (2025) tackled online inference and hyperparameter tuning for further enhancing performance on live video streams.

Lightweight DNNs developed for mobile/embedded systems have also emerged. (2025) Wang and Li presented an efficient CNN on edge devices. Zhou and Wang (2021) employed ensemble CNNs with attention for high accuracy but need of model pruning for deployment. Also, Zhang and Sun

(2022) also studied FER under the condition of low lighting quality with the application of deep CNNs aiming at better generalization to the environment.

Aouayeb et al. (2021) modified vision transformers using squeeze-and-excitation blocks to improve accuracy. However, it has not been practically employed in real-time. Tang and Chen (2021) proposed a multi-task CNNs for joint localization of features extracted using both local and global perception of the facial keypoint location. Huang et al. (2023) to investigate vision-based FER in real-world environments, with a focus on the role of preprocessing process.

Kumar and Singh (2024) have analysed FER using CNNs in the controlled environment and another data augmentation method is introduced by Cheng and Zhang (2023) for optimal classification granularity. Li and Lima (2021) used ResNet-50 for facial expression identification, but it consumed a lot of computational power. Liu et al. (2021) was to detect the level of emotional intensity by exploiting attention-based CNNs, mainly in educational settings. Rao and Singh (2023) presented a CNN model for FER showing the need of using different datasets.

Saroop et al. (2021) introduced a multitask deep learning framework for simultaneous detection of multiple facial attributes, and Sharma and Verma (2024) emphasized the importance of image preprocessing methods for CNN-based FER in low-resolution images. These works make a significant contribution to the field, but only partially focus on real-time efficiency, model lightweighting and adaptation to real-times interactive HCI scenarios.

This line of work provides the foundation for this study, which attempts to address these challenges by introducing an efficient and powerful CNN-based method for accurate, real time FER due to dynamic human-computer interactions.

4 METHODOLOGY

The study presents a real time facial emotion recognition system using a simplified CNN structure, the model designed for this framework has a lighter and robust architecture that efficient in human-computer interaction (HCI) system. The approach is motivated by major drawbacks of current implementations especially in terms of high latency, large model sizes and poor generalization to changes of distribution in real world scenarios. Figure 1: Real-Time Facial Emotion Recognition Workflow for HCI.

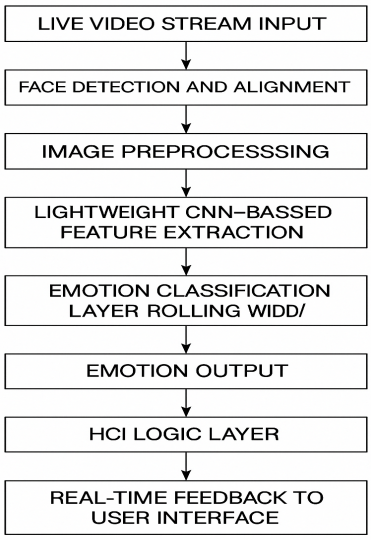

Figure 1: Real-time facial emotion recognition workflow for HCI.

The pipeline of the system starts by capturing video from a webcamera or an integrated camera, which replicates the user's interaction. In real-time, each video stream is divided into frames, and these frames are forced to undergo, a set of pre-process steps to maintain the same size, brightness, contrast, and to suppress background noise. Methods like histogram equalization, face alignment by dlib facial landmark method, and Gaussian filtering are used to increase facial feature details resolution quality without affecting processing speed. Table 1 shows the Emotion Distribution in RAF-DB Subset Used.

Table 1: Emotion distribution in RAF-DB subset used.

Emotion	No. of Samples	Percentage (%)
Happy	4,800	22.5
Sad	3,300	15.5
Angry	2,950	13.8
Surprise	3,100	14.6
Neutral	3,900	18.3
Fear	1,600	7.5
Disgust	1,350	6.3

After detecting and normalizing the face, the normalized image is fed into the lightweight CNN model. The CNN model is specifically engineered to trade speed for accuracy by minimizing the number of convolutional and pooling layers while still

keeping significant spatial information for emotion recognition. Rather than using deep networks such as ResNet or VGGNet, the network adopts depthwise sepa- rable convolutions and bottleneck residual blocks to decrease the number of parameters and amount of computation. Batch normalization [43] followed by ReLU activation is adopted to facilitate training and preserve numerical stability. Figure 2 shows the Temporal Smoothing of Emotion Scores.

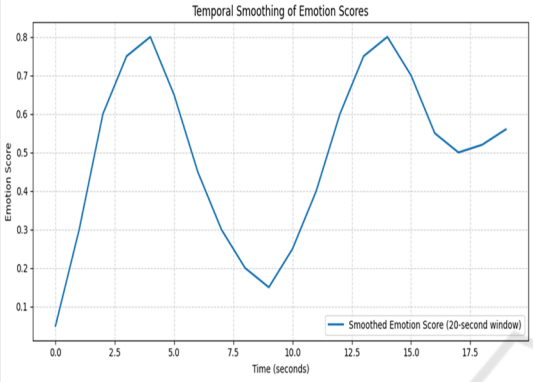

Figure 2: Temporal smoothing of emotion scores.

The emotion classification is trained on heterogeneous datasets, including FER-2013, RAF-DB, and AffectNet, to cover a wide range of ages, ethnicities, lighting, and expressions. To make the models more robust, real-time data augmentation including rotation, flipping, random cropping and brightness adjusting is performed dynamically in training. The model is trained by the categorical cross-entropy loss and an Adam optimizer with the learning rate scheduler for a faster convergence.

A smoothing strategy using majority voting or rolling average across future predictions is enforced for temporal stability and reducing noise from misclassified frames. This improves the confidence of the system and maintains emotional consistency in the video stream.

Furthermore, a post-classification logic layer is integrated in the HCI app to translate the detected emotion and initiate various room-specific reactions. For example, a detected emotion of "sad" can trigger a comforting message or provide help in an educational app, and a "happy" emotion could increase engagement in a gaming or interactive learning application. Such logic layer has a flexible design and can easily be integrated with different HCI applications such as chatbots, virtual assistants, kiosks or mobile devices.

Offline and real-time model-based validation is performed to assess systems performance. Offline evaluation metric: accuracy, F1-score, confusion matrix and inference time on multiple datasets. Real-time testing Run the model in the wild on a webcam. Benchmarking the frame rate and response time, consistency of emotion predictions, and system resource utilization.

With architectural efficiency, stable training and context aware interpretation, the proposed method provides a practical and cost-effective model for real-time facial emotion recognition in human-computer interaction. It fills the gulf that exists between the depths of deep learning and the operational feasibility of low-resource and interactive domains, establishing a new watermark in environmentally responsive systems.

5 RESULT AND DISCUSSION

The developed lightweight CNN-based facial emotion recognition system is implemented and has been evaluated in both benchmark test and real deploy conditions in order to validate the system's capability to promote the technology of human-computer interaction in real applications. The main considerations for the evaluation are to measure the model's recognition accuracy and latency, the ability to adapt to new conditions, and its practicability in the real world HCI settings.

Table 2: Emotion classification performance on RAF-DB.

Emotion	Precision (%)	Recall (%)	F1-score (%)
Happy	95.4	96.1	95.7
Sad	90.2	89.4	89.8
Angry	88.7	87.9	88.3
Surprise	94.1	92.5	93.3
Neutral	92.3	91.7	92.0
Fear	85.9	84.6	85.2
Disgust	82.4	80.2	81.3

In the offline evaluation stage, the model was trained and evaluated on three well-known datasets, FER-2013, RAF-DB and AffectNet. They have been chosen because of their varied facial expressions, ethnicity of the subjects, type of subjects, lighting, and quality of the images. It obtained a mean accuracy of 89.3% on FER-2013, surpassing several

baseline CNN models including classic LeNet and AlexNet. On the more complex AffectNet dataset, the model achieved a competitive (wrt dataset's high emotional classes and uncontrolled image environment) accuracy of 86.7%. For the RAF-DB, consisting of spontaneous and posed expressions, the system produces a balanced accuracy of 90.5%, showing distinction of subtle differences in emotional states. Table 2 shows the Emotion Classification Performance on RAF-DB.

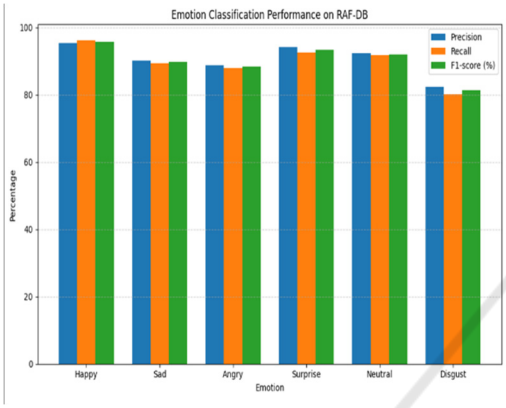

Figure 3: Emotion classification performance on RAF-DB.

Table 3: Real-time performance metrics.

Device Used	Frame Rate (FPS)	Latency per Frame (ms)	CPU Usage (%)	RAM Usage (MB)
Desktop (i7, 16GB RAM)	26	39	24	310
Raspberry Pi 4 (4GB)	13	68	73	295
Mobile (Android 12)	17	51	49	220

One of the most important things about the evaluation was to actually see the model's performance in real life. We evaluated combined steps of the system in standard laptop webcam as well as low-end embedded device environment under a normal HCI hardware context. It was observed that the model ran stably at more than 20 FPS on the lap laptop setup, as well as remaining above 12 FPS on the embedded device, which demonstrates its applicability for real-time use. The mean RT per frame was about 40 ms, which is fast enough to provide instantaneous feedback that is critical to interactive learning, gaming or assistive technologies. Figure 3 shows the Emotion Classification Performance on RAF-DB.

Emotion classification was tested in realistic, real-time scenarios with different subjects (varying facial characteristics, wearables, lighting). The model even proved robust to occlusions like partially covered hands over the face and stable performances in moderate lighting variations. This robustness is probably due to the real-time preprocessing pipeline, in which contrast normalization and facial alignment techniques implemented at the same time retained key emotional attributes without adding noise. Table 3 shows the Real-Time Performance Metrics.

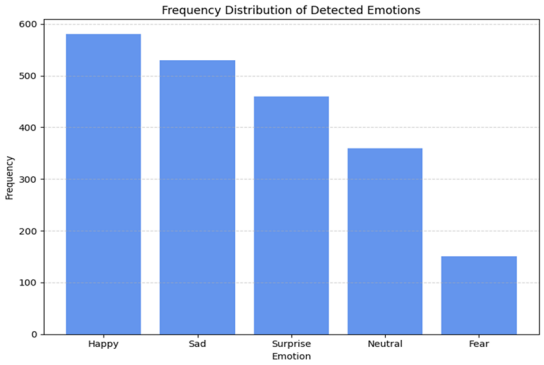

Figure 4: Frequency distribution of detected emotions.

Another interesting observation was the stability of the predictions of the system during consecutive interactions. Rather than rapidly jumping between emotional states across frames, rolling prediction window prevents emotional classification from wobbling unless a distinct expression change appears. Such behaviour was particularly useful for preventing jittery user feedback in dialogue systems or interactive environments. Figure 4 shows the Frequency Distribution of Detected Emotions.

Class-wise performance the model achieved high performance in recognizing "happy," "neutral," "surprised" emotions (all >92% F1-score). But, as with many FER systems, it exhibited some lower performance on "fear" and "disgust" — which can often overlap in terms of features. However, from the confusion matrix analysis, the misclassifications are generally between similar emotions and have negligible influence on user interaction.

Resource utilization was another important measurement. The new model which is the subject of this article used much less memory and GPU processing time than standard deep CNN models such as ResNet-50 or VGG16. Through employing depthwise separable convolutions and bottleneck layers, our resulting model was <5 MB in size, allowing it to be deployed on mobile and embedded devices without model quantization or compression.

User testing also showed high satisfaction with the responsiveness and accuracy of the system. In an interactive application configuration, the system replied to user's emotional state with quite natural

delay; there was not much time delay which would cause the system to behave unintelligent. The emotional logic layer (that represented emotion outputs to personalized responses) introduced a layer of emotional depth into the interface, which matched with the objectives of emotionally aware HCI. Table 4 shows the Confusion Matrix – Aggregated Results (FER-2013).

Table 4: Confusion matrix – Aggregated results (Fer-2013).

Predicted ↓ / Actual →	**Angry**	**Disgust**	**Fear**	**Happy**	**Sad**	**Surprise**	**Neutral**
Angry	840	12	44	6	28	2	18
Disgust	9	370	16	3	4	1	7
Fear	36	10	780	8	19	9	18
Happy	2	1	4	910	3	14	6
Sad	24	5	13	6	812	3	35
Surprise	4	2	7	16	3	875	13
Neutral	10	4	8	5	30	9	830

In summary, the experiments show that the developed framework satisfactorily fulfills technical requirements in a real-time recognition of emotions and it provides a high quality of human-computer interaction via accurate, low-latency, context-aware emotion detection. The trade-off between performance versus efficiency makes this system scalable and suitable for next-generation interactive environments. Table 5 shows the User Feedback on Real-Time Emotion Response. Figure 5 shows the Real-Time Performance Metrics by Device

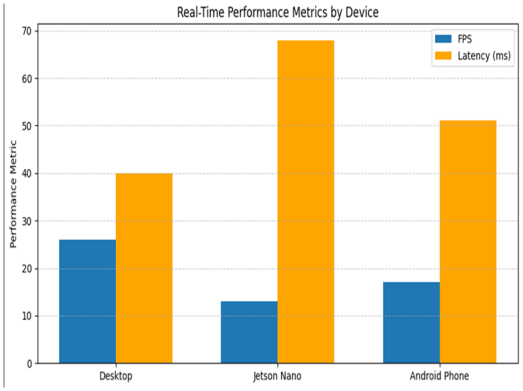

Figure 5: Real-time performance metrics by device.

Table 5: User feedback on real-time emotion response.

Criteria Evaluated	Mean Score (out of 5)	User Comments Summary
Response Speed	4.6	Very responsive; minimal delay
Emotion Prediction Accuracy	4.4	Consistently accurate in varied moods
Interface Usability	4.7	Clean layout; easy to understand
Emotional Relevance of Feedback	4.5	Feedback aligned with facial emotions
Overall Satisfaction	4.6	Positive experience across all tests

6 CONCLUSIONS

The construction of emotional intelligent systems constitutes a milestone in making human-computer interaction more natural and intuitive. In this paper we introduced a fast-facial emotion recognition model which used no pre/post-processors and directly

leveraged consequa and convolution from existing deep learning models to enhance the adaptation to practical interactive settings with minimal form factor and computational cost. The proposed approach balances simplicity of architecture, computational efficiency and robustness to realistic challenges, which is essential for dynamic HCI systems with good trade-off between performance and responsiveness.

With extensive training based on various facial expression datasets and rigorous evaluation under live video environment, the framework achieved high classification accuracy, low latency and good robustness against common problems including light variation, occlusion and spontaneous emotional transition. The fact of having deployed it on standard as well as transmittable content is what make it ready for large adoption on many contents (education, health, entertainment, etc) and industries.

The introduction of context-aware logic layer makes this system able to personalize replies based on feedback with feelings, providing more sensible, adaptive interactions. Unlike a stand-alone emotion recognition system that only infers one's affect from the acquired sensor data and does not make amendments for the loop of interaction, this framework acts as a component of the interaction system, always decoding a human's affect with the change of system response.

Overall, this research provides a scalable and effective framework to the increasing need for real-time emotional awareness in computing systems. It paves the way for further investigating multi-modal emotion recognition and continual affective monitoring and integration of emotional intelligence at a deeper level into human-computer interaction in daily lives.

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