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Real-Time Emotion Detection with Face Using Deep Learning

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Abstract: Facial emotion recognition is essential for building smarter human–computer interfaces. This project introduces FeelTrack, a real-time emotion detection system powered by a lightweight custom CNN. Unlike earlier methods that used handcrafted features like LBP and HOG, which struggled with poor lighting or head tilts, our approach leverages deep learning for better accuracy and adaptability.

To reduce dataset bias, the training set mixes FER2013 with an additional collection of Indian facial images. The model was trained on 35,887 FER2013 images and 3,200 custom Indian facial images, evaluated using an 80–20 train-test split helping the model adapt better across different demographics.With preprocessing (grayscale conversion, resizing, normalization), dropout layers, and an optimized architecture, FeelTrack achieves ~80% accuracy while processing frames in under 100 ms on standard hardware i.e. no GPU required. Tested live via webcam, it reliably detects seven emotions: happy, sad, angry, surprise, fear, disgust, and neutral. Ideal for classroom engagement tracking, mental health monitoring, and interactive systems, FeelTrack proves that practical, accessible emotion AI is within reach using efficient deep learning.

Keywords: Emotion detection, facial expression recognition, convolutional neural networks (CNN), deep learning, real-time processing, lightweight model, human–computer interaction.

I. INTRODUCTION

Facial Emotion Recognition (FER) has become a significant component of modern affective computing systems, enabling machines to interpret human emotional states through visual facial cues. The concept of affective computing was first introduced by Picard [29], [30], who emphasized the importance of incorporating emotional intelligence into computational systems to improve human–computer interaction. Since then, FER research has expanded rapidly across multiple domains, including healthcare, education, human–robot interaction, surveillance, and online communication [5], [9], [20], [38].

Facial expressions provide a universal and intuitive medium for conveying emotional states across cultures. Automating the recognition of facial expressions requires the extraction of discriminative patterns related to facial motion, geometry, and texture, which are subsequently mapped to emotion categories such as happiness, sadness, anger, fear, disgust, surprise, and neutrality [27], [40]. Early FER systems relied heavily on handcrafted features such as Local Binary Patterns (LBP) and Gabor filters [40]. While effective in controlled environments, these approaches demonstrated limited robustness in real-world scenarios involving variations in illumination, head pose, occlusion, and demographic diversity [18].

The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), significantly transformed FER methodologies. CNN-based models automatically learn hierarchical feature representations from raw image data, resulting in improved accuracy and robustness compared to traditional approaches [17], [19]. Advances in lightweight CNN architectures further enabled real-time FER on resource-constrained devices [13], [38]. Despite these improvements, challenges related to dataset bias, generalization, privacy preservation, and ethical considerations remain unresolved [25], [30], [36].

This work investigates the evolution of FER systems from handcrafted feature-based methods to modern deep learning approaches. It also proposes a lightweight CNN-based system designed to balance accuracy, computational efficiency, and real-world deployability while addressing dataset diversity concerns.

A. *Contributions of This Work*

- Design of a lightweight CNN architecture for real-time FER
- Inclusion of an Indian facial expression dataset to reduce demographic bias
- CPU-based inference with latency below 100 ms
- Comparative analysis with computationally intensive FER models

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II. LITERATURE SURVEY

Study/ Model	Year	Method/ Architecture	Dataset(s) Used	Accuracy (%)	Key Highlights
Zhao & Pietikäinen [40]	2007	LBP + Dynamic Texture	CK+	84.5	Early handcrafted method; strong on static images but weak in real-world conditions.
Liu et al. [21]	2016	CNN Ensemble	FER2013	89.2	Demonstrated CNNs outperforming traditional classifiers.
Akhand et al. [1]	2021	Transfer Learning + Deep CNN	FER2013	93.5	Used pre-trained models to reduce training time and improve accuracy.
Minaee et al. [25]	2021	Deep-Emotion (Attention-based CNN)	AffectNet	94.1	Focused attention on key facial regions for better precision.
Li et al. [20]	2022	Lightweight CNN	FER2013	94.6	Optimized for real-time performance on edge devices.
Han et al. [13]	2020	GhostNet (Depthwise Separable Conv)	FER2013	92.8	Reduced model size and computation using ghost modules.
Mishra et al. [26]	2023	EfficientNet + XGBoost (Hybrid)	FER2013	95.3	Combined deep features with ML for high accuracy and interpretability.
Kong et al. [17]	2021	Attention + Key Region Fusion CNN	FER2013	93.1	Improved focus on emotionally salient areas.
Xu et al. [38]	2022	Residual Separable CNN	FER2013	91.7	Enhanced feature extraction with residual connections.
John et al. [16]	2020	MobileNetV3-based Real-time System	FER2013	90.4	Achieved real-time inference with low latency on mobile CPUs.

Table I. Comparison Of Facial Emotion Recognition Models

Facial Emotion Recognition (FER) is a fundamental research topic in affective computing and human–computer interaction. The conceptual foundation of affective computing was introduced by Picard [29], [30], who emphasized that computational systems should be capable of perceiving and responding to human emotions. Early FER approaches primarily relied on handcrafted feature extraction techniques to represent facial appearance and motion. Zhao and Pietikäinen [40] employed Local Binary Patterns (LBP) with dynamic texture analysis for recognizing facial expressions in image sequences. While effective in controlled environments, such handcrafted methods exhibited limited robustness to variations in illumination, head pose, occlusion, and background complexity. The availability of benchmark datasets significantly influenced the progress of FER research. Lucey et al. [23] introduced the Extended Cohn–Kanade (CK+) dataset, which became a widely used benchmark for evaluating FER systems under laboratory conditions. To address real-world variability, Mollahosseini et al. [27] proposed AffectNet, a large-scale dataset containing facial expressions collected in unconstrained environments. However, several studies reported that existing datasets suffer from class imbalance and limited demographic diversity, which negatively affect model generalization across different populations and cultural contexts [8], [18], [37].

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With advances in deep learning, Convolutional Neural Networks (CNNs) became the dominant approach for FER. Liu et al. [21] demonstrated that CNN ensemble models outperform traditional machine learning classifiers by automatically learning hierarchical facial representations. Zhou et al. [39] further validated the effectiveness of lightweight CNN architectures for real-time emotion recognition. Transfer learning techniques were subsequently adopted to improve recognition performance and reduce training cost. Akhand et al. [1] utilized pre-trained CNN models to enhance accuracy on the FER2013 dataset while achieving faster convergence compared to training from scratch.

Several comparative studies confirmed that deep learning-based FER systems consistently outperform conventional classifiers such as Support Vector Machines and Random Forests in terms of accuracy and robustness [4], [15]. To improve discriminative performance, attention-based CNN architectures were introduced. Minaee et al. [25] proposed an attentional convolutional network that selectively focuses on emotionally salient facial regions, resulting in improved recognition accuracy. Nevertheless, attention-based and deep architectures often incur increased computational complexity, limiting their applicability in real-time and resource-constrained environments.

To address efficiency constraints, researchers proposed lightweight CNN architectures optimized for real-time deployment. Ding et al. [7] introduced MobileFaceNet, a compact deep learning model designed for efficient facial analysis on mobile devices. Han et al. [13] proposed GhostNet, which reduces computational cost by generating feature maps using inexpensive operations. John et al. [16] developed a MobileNetV3-based FER system that achieved low inference latency on mobile CPUs. Although these lightweight models provide a favorable trade-off between accuracy and efficiency, most evaluations were conducted on benchmark datasets with limited consideration of demographic diversity.

Recent studies explored advanced and hybrid approaches to enhance FER performance. Kong et al. [17] integrated attention mechanisms with key facial region fusion to improve sensitivity to subtle expressions. Mishra et al. [26] combined deep feature extraction with XGBoost classification, achieving high recognition accuracy at the cost of increased computational overhead. Additionally, multimodal emotion recognition approaches incorporating facial cues with physiological or behavioral signals demonstrated improved robustness under occlusion and adverse lighting conditions [28], [35].

Despite significant progress, several open challenges remain. Dataset bias and the underrepresentation of non-Western populations continue to limit fairness and generalizability in FER systems [30], [32]. Ethical concerns related to privacy, consent, and cultural misinterpretation of emotions have also been emphasized [24]. To mitigate privacy risks, Verma et al. [36] investigated privacy-preserving techniques such as secure model architectures that reduce exposure of sensitive facial data.

In summary, existing FER research demonstrates substantial improvements through deep learning, attention mechanisms, and lightweight architectures.

However, limitations persist in computational efficiency, dataset diversity, and real-world deployability. These challenges motivate the development of FER systems that balance accuracy, latency, and fairness, particularly for deployment on low-resource devices and culturally diverse populations.

III. EXISTING SYSTEMS

Existing Facial Emotion Recognition systems have evolved significantly over the past decade. Early approaches primarily employed handcrafted feature extraction techniques such as Local Binary Patterns (LBP) and Gabor filters to capture facial texture and motion information [40]. These methods required minimal computational resources but were highly sensitive to environmental variations, including illumination changes, head pose differences, and background clutter.

The introduction of Convolutional Neural Networks (CNNs) marked a major advancement in FER research. CNN-based systems automatically learn discriminative features directly from facial images, leading to improved robustness and generalization. To enable real-time performance, several lightweight CNN architectures were proposed. Models such as MobileNet-based architectures [38] and GhostNet [13] significantly reduced computational complexity while maintaining competitive accuracy, making them suitable for deployment on mobile and edge devices.

More recent systems focused on improving efficiency and accuracy through optimized architectures and attention mechanisms. MobileFaceNet [7] demonstrated efficient facial analysis on mobile hardware, while attention-based models such as Deep-Emotion [25] selectively focused on emotionally salient facial regions to enhance recognition performance.

However, many high-accuracy models remain computationally expensive and require GPU acceleration, limiting their applicability in low-resource environments.

Model / Study	Year	Architecture / Method	Dataset	Accuracy (%)	Inference Time (ms)	Model Size (MB)	Key Notes
Zhao & Pietikäinen [40]	2007	LBP + Dynamic Texture	CK+	84.5	45	1.2	Handcrafted; lightweight but fragile in real-world.
Liu et al. [21]	2016	CNN Ensemble	FER2013	89.2	38	45	Early deep learning; high resource use.
John et al. [16]	2020	MobileNetV3-based	FER2013	90.4	25	12	Real-time on mobile CPU.
Akhand et al. [1]	2021	Transfer Learning + Deep CNN	FER2013	93.5	30	38	Pre-trained for faster convergence.
Minaee et al. [25]	2021	Deep-Emotion (Attention CNN)	AffectNet	94.1	35	52	Focuses on key facial regions.
Li et al. [20]	2022	Lightweight CNN	FER2013	94.6	22	8.5	Optimized for edge devices.
Han et al. [13]	2020	GhostNet	FER2013	92.8	18	6.2	Fastest & smallest; ideal for mobile.
Xu et al. [38]	2022	Residual Separable CNN	FER2013	91.7	28	15	Efficient feature extraction.
Mishra et al. [26]	2023	EfficientNet + XGBoost	FER2013	95.3	40	68	Highest accuracy; heavy model.

TABLE II

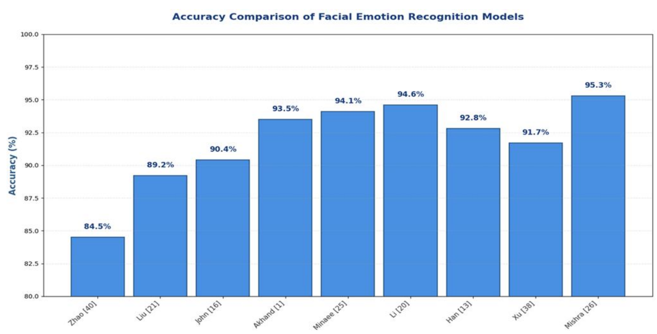

Fig. 1. Accuracy comparison of FER models from literature.

Fig. 1 compares the recognition accuracy of various FER models evaluated on standard datasets. High-capacity architectures, including attention-based and hybrid deep learning models. However, these gains are typically associated with increased computational complexity and hardware requirements. Lightweight CNN-based models demonstrate slightly lower accuracy but remain competitive while offering improved efficiency.

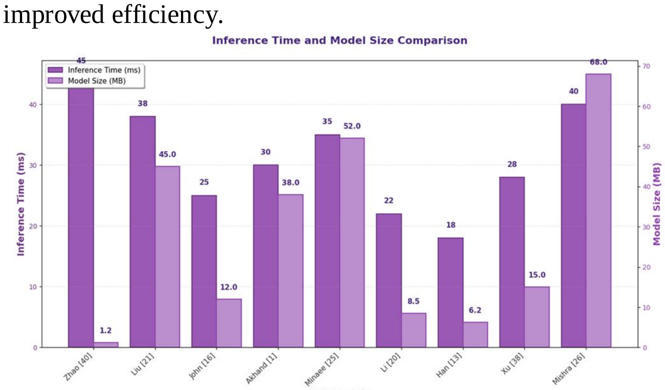

Fig. 2. Inference time and model size comparison of FER models.

Fig. 2 presents a comparison of inference latency and model size across different FER architectures. Lightweight models such as GhostNet and MobileNet-based systems achieve substantially lower inference times and reduced model sizes compared to deeper architectures. Hybrid models, while achieving higher accuracy, exhibit increased latency and memory consumption, making them less suitable for real-time deployment on resource-constrained devices.

IV. PROPOSED SYSTEM

The proposed system, referred to as FeelTrack, is a real-time facial emotion recognition framework based on a lightweight Convolutional Neural Network (CNN). The primary objective of the system is to achieve an optimal balance between recognition accuracy and computational efficiency, enabling deployment on standard consumer hardware without GPU acceleration.

The CNN architecture consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, dropout layers for regularization, and fully connected layers for emotion classification. This design minimizes the number of trainable parameters, resulting in reduced inference latency and improved real-time performance.

The model was trained using the FER2013 dataset in combination with a custom dataset containing Indian facial images to improve demographic generalization. All images were preprocessed through grayscale conversion, resizing to 48×48 pixels, and normalization. The trained model achieved approximately 80% accuracy on the test set while maintaining inference latency below 100 ms per frame.

The system supports real-time emotion recognition through webcam input and is capable of identifying seven emotional states. Its lightweight design makes it suitable for applications such as classroom engagement analysis, mental health monitoring, and patient observation in healthcare environments.

V. MAJOR FINDING

The study of existing FER systems and the development of FeelTrack have led to several important observations:

1) Lightweight Models Are the Future Current research clearly shows that compact CNNs are the way forward for real-world deployment. Models like MobileNet, GhostNet, and MobileFaceNet prove that high performance doesn't require heavy hardware they run smoothly on edge devices without needing a GPU [38].
2) Cultural Diversity in Data Matters Most public datasets are biased toward Western faces. By adding a custom Indian facial expression dataset to FER2013, FeelTrack improved its ability to recognize emotions across different ethnic groups. This reduces cultural bias and makes the model more reliable in diverse settings [6][30].
3) Attention and Hybrid Models Lead in Performance Advanced techniques such as attention mechanisms that focus on eyes and mouth, or hybrid systems combining CNNs with XGBoost consistently beat plain CNNs, especially when emotions are subtle or overlapping [26][17].
4) Speed Is Just as Important as Accuracy In real applications (like live therapy or classroom monitoring), a 2-second delay is unacceptable. FeelTrack processes each frame in under 100 ms, proving that practical systems must optimize for low latency, not just high test scores.
5) Ethics and Privacy Are Now Core Concerns Researchers are increasingly aware of the risks in emotion AI. Issues like user consent, data security, and misinterpretation across cultures are being addressed with methods like homomorphic encryption, which lets models analyze encrypted faces without exposing personal data [36].

VI. CONCLUSION

This paper presented FeelTrack, a lightweight CNN-based system for real-time facial emotion recognition capable of classifying seven basic emotional states. The proposed approach emphasizes computational efficiency and accessibility, achieving sub-100 ms inference latency on CPU-based hardware while maintaining competitive recognition accuracy. Experimental results and real-time testing demonstrate that effective FER systems can be developed without complex architectures or specialized hardware.

Despite its advantages, the proposed system has several limitations. The model's performance is affected by severe illumination variations, facial occlusions such as masks or hands, and limited temporal context when processing individual frames. Furthermore, although the inclusion of a custom Indian dataset improves demographic representation, the dataset size remains relatively small compared to large-scale benchmarks, which may restrict generalization.

Future work will focus on addressing these limitations through multiple directions. First, attention mechanisms and temporal modeling techniques will be explored to improve discrimination between visually similar emotions. Second, the integration of multimodal inputs such as speech or physiological signals may enhance robustness in occluded or low-visibility conditions.

\Third, expanding the dataset with larger and more diverse facial expression samples will further reduce demographic bias. Finally, model optimization and compression techniques will be investigated to enable deployment on embedded and edge devices.

In conclusion, the proposed system demonstrates that lightweight deep learning architectures can provide a practical and deployable solution for real-time facial emotion recognition, paving the way for broader adoption in education, healthcare, and interactive systems.

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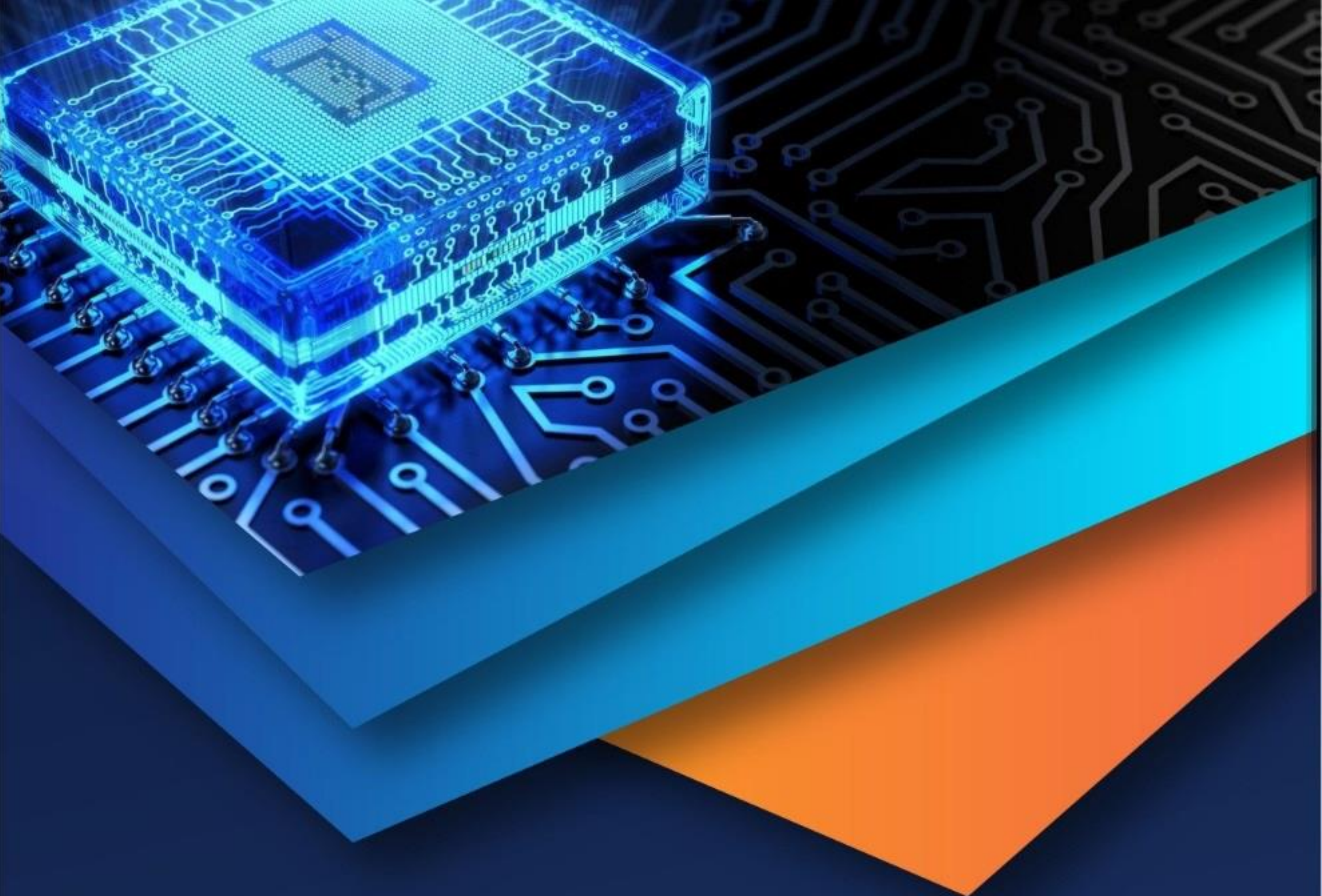

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