

ADVANCED HUMAN EMOTION DETECTION USING FACIAL FEATURES AND DIGITAL IMAGE PROCESSING TECHNIQUES

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Abstract

This research presents a novel Human Emotion Detection utilizing Facial Features (HEDFF) framework that integrates deep learning, optimization techniques, and advanced image processing for highly accurate emotion recognition. The proposed framework employs the AffectNet Dataset, a large-scale and diverse dataset containing richly annotated facial expressions, to enhance the robustness and generalization capability of the model. A key novelty of this study lies in the hybrid integration of Gabor filtering, Recurrent Neural Networks (RNNs), EfficientNet architecture, and Particle Swarm Optimization (PSO) within a unified emotion detection pipeline. During preprocessing, Gabor filtering effectively extracts discriminative texture and edge information from facial images, improving feature representation under varying illumination and expression conditions. The RNN component captures temporal dependencies and sequential facial dynamics, enabling better understanding of subtle emotional transitions. Furthermore, the EfficientNet model provides a computationally efficient yet highly accurate classification mechanism through optimized scaling of network depth, width, and resolution. To further enhance system performance, PSO is applied for automated hyperparameter optimization, reducing computational complexity while maximizing classification accuracy. Unlike conventional emotion recognition systems that rely solely on static facial features or single deep learning architectures, the proposed HEDFF framework combines spatial, temporal, and optimization-based learning strategies to achieve superior robustness and precision. Experimental evaluations conducted on benchmark datasets demonstrate the effectiveness of the proposed approach, achieving a remarkable accuracy of 98.87%, precision of 97.11%, sensitivity of 95.15%, and specificity of 96.96%, outperforming several existing state-of-the-art methods. The proposed framework offers significant contributions to the fields of affective computing, intelligent human-computer interaction, healthcare monitoring, mental health assessment, and real-time emotion-aware applications.

Keywords: Deep Learning, Gabor filtering, Recurrent Neural Network (RNN), Particle Swarm Optimization (PSO).

1.Introduction

In the vast realm of human communication, emotions are integral, shaping our interactions, decisions, and relationships. They form a complex, interwoven tapestry that influences how we respond to the world around us. While understanding and interpreting emotions has long been a challenge, recent advancements in artificial intelligence have revolutionized this domain. One particularly groundbreaking area is the detection of human emotions through facial features. Facial expressions, from a subtle smile to a furrowed brow, serve as powerful indicators of emotional

states, forming the foundation of non-verbal communication. Leveraging AI to analyze these expressions unlocks new possibilities across diverse fields, including human-computer interaction, healthcare, and psychology.

Human emotion detection (HED) has emerged as a multidisciplinary field, integrating psychology, artificial intelligence, and digital image processing. The ability to accurately interpret emotions from facial expressions has far-reaching applications in areas such as healthcare, market research, and human-computer interaction. The development of HED systems relies on both theoretical insights

into emotion analysis and the practical implementation of advanced image processing techniques to enhance detection accuracy and efficiency. As technology continues to evolve, the intersection of AI and emotion recognition presents exciting opportunities to deepen our understanding of human emotions and their impact on daily life.

Emotions serve as a universal language, transcending cultural and linguistic boundaries. They provide vital cues that shape social interactions, influence perceptions, and guide responses to the world around us. The ability to recognize and understand emotions fosters empathy, strengthens communication, and enhances interpersonal relationships. As a result, emotion detection holds significant potential across various domains, including human-computer interaction, virtual reality, mental health assessments, and customer service. Throughout history, the ability to interpret emotions has been crucial for human survival—helping our ancestors distinguish threats from friendly gestures and assess the sincerity of others, a skill that remains just as relevant in modern society.

Traditionally, emotions were gauged through verbal and non-verbal cues. However, the limitations of these methods prompted the exploration of technological solutions, with facial features emerging as a rich and reliable source of emotional information. The human face functions as a dynamic canvas, reflecting a spectrum of emotions through subtle variations in expression, gaze, and micro-movements. With advancements in computer vision and machine learning, researchers are now developing sophisticated algorithms to analyze these facial cues, leading to more accurate and nuanced emotion detection systems. Facial expressions, driven by a complex interplay of facial muscles, serve as powerful indicators of emotions ranging from joy and surprise to sadness and anger. Deciphering these expressions involves analyzing key facial features, such as the eyes, eyebrows, nose, and mouth, to gain deeper insights into human emotions.



Figure 1: Depiction of Facial Emotion Expressions

Digital image processing is fundamental to extracting and analyzing facial features for emotion detection. By leveraging cameras and sensors, computer vision algorithms can capture and interpret facial expressions in real time, offering a dynamic understanding of emotional states. As a subset of computer vision, facial recognition technology has advanced significantly in recent years [8][9]. Modern systems employ deep learning techniques to extract high-level features from facial images, enhancing the accuracy and robustness of emotion detection. While Convolutional Neural Networks (CNNs) are widely used for hierarchical visual feature extraction, Recurrent Neural Networks (RNNs) have gained traction for their ability to process sequential data, making them particularly useful for tracking temporal changes in facial expressions over time.

A crucial component of emotion detection is facial landmark detection, which identifies key reference points to analyze facial expressions and movements [10]. The growing field of Human Emotion Detection (HED) has seen remarkable advancements, particularly through facial feature analysis. This research introduces a Human Emotion Detection using Facial Features (HEDFF) framework, emphasizing the integration of the AffectNet dataset. Facial expressions are a primary means of conveying emotions, making their analysis essential for improving emotion recognition accuracy. The AffectNet dataset, known for its diversity and extensive annotations, provides a robust foundation for training and evaluating our framework.

II.Literature Survey

Recent advancements in Facial Emotion Recognition (FER) have significantly improved the accuracy, robustness, and computational efficiency of emotion detection systems through the integration of deep learning, attention mechanisms, and hybrid architectures. Recent studies emphasize the importance of combining spatial, temporal, and semantic feature extraction techniques to achieve higher recognition performance across diverse datasets.

For instance, Nwankpa et al. (2024) introduced ResEmoteNet, a hybrid framework integrating Convolutional Neural Networks (CNNs), Residual Networks, and Squeeze-and-Excitation (SE) blocks to improve feature representation and reduce information loss during training. Their model demonstrated enhanced recognition accuracy on the AffectNet-7 dataset by effectively

recalibrating important facial features and overcoming vanishing gradient issues in deep architectures. Similarly, Rashwan and Ramadan (2025) proposed EmoNeXt, an adapted ConvNeXt-based architecture integrated with Spatial Transformer Networks (STNs) and SE layers to focus on salient facial regions and improve generalization under varying lighting conditions and occlusions.

Several researchers have also explored hybrid preprocessing and feature extraction approaches to improve FER performance. Hemalatha and Senthil Kumar (2024) developed a Gabor Filter-CNN hybrid model, where Gabor filters were applied during preprocessing to capture orientation and texture information before CNN classification. Their model achieved an impressive accuracy of 99.85% on the CK+48 dataset, demonstrating the effectiveness of combining handcrafted texture descriptors with deep learning techniques. Likewise, Qian and Huang (2024) proposed the Informative and Discriminative Semantic Feature Learning (IDSFL) framework, which integrates Gabor feature extraction, Emotion-aware Attention Modules (EAM), and Global-Local Feature Fusion to enhance robustness against head pose variations and facial occlusions.

The integration of temporal learning mechanisms has further improved emotion recognition capabilities in dynamic environments. Mehta and Rao (2025) proposed a hybrid CNN-RNN model, where CNNs extracted spatial facial features while Recurrent Neural Networks (RNNs), particularly LSTMs, modeled temporal emotional transitions across sequential facial frames. Although the system achieved moderate accuracy, the study highlighted the importance of temporal modeling in real-time emotion monitoring applications. In another study, Li et al. (2024) enhanced the lightweight GhostNet architecture by integrating Transformer Encoder Blocks and attention mechanisms, resulting in the Enhanced GhostNet Transformer (EGT) model. Their approach significantly improved efficiency and classification accuracy on RAF-DB and AffectNet datasets while remaining suitable for mobile and edge devices.

Researchers have also focused on improving class separability, interpretability, and practical applications of FER systems. Shirakabe et al. (2024) introduced a framework combining ResNeXt and EfficientNet with the ArcFace loss function to address data imbalance and improve intra-class compactness in AffectNet expression recognition. Furthermore, Mahajan and Singh (2025) explored Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM and LIME to analyze whether CNN-based FER models exhibit human-like attention behavior during emotion classification. Their findings demonstrated that deep learning models often focus on facial regions similar to those emphasized by humans during emotional interpretation.

Additionally, FER has shown promising applications in healthcare and mental health assessment. Sethi et al. (2024) developed FacialNet, which combines UNet-based facial segmentation with transfer learning models such as ResNet50 and MobileNetV2 to support mental health analysis through real-time emotion monitoring. The model achieved strong performance on FER2013 and CK+ datasets, highlighting the growing role of FER systems in clinical and therapeutic environments. Standard CNN-based approaches also remain relevant for real-time applications. Bhat and Sheikh (2024) demonstrated that a conventional CNN architecture trained on FER2013

could achieve reliable emotion classification performance in constrained real-time environments, further validating the effectiveness of CNNs in facial expression analysis.

Overall, the literature demonstrates a clear trend toward hybrid deep learning architectures, attention-based mechanisms, explainable AI, and lightweight optimized models for FER systems. These advancements collectively contribute to higher recognition accuracy, improved robustness under challenging conditions, and broader applicability in real-time human-computer interaction, healthcare, surveillance, and affective computing systems. Although significant progress has been achieved in Facial Emotion Recognition systems, many existing methods focus only on spatial or temporal feature extraction independently. Most traditional methods lack integrated optimization techniques, computational efficiency, and robustness against varying illumination, pose variations, and facial occlusions. Therefore, there is a need for a unified framework capable of combining texture enhancement, temporal learning, lightweight classification, and hyperparameter optimization for robust real-time emotion detection.

III Related Work

To enhance emotion classification, our approach integrates Gabor filtering for feature enhancement, CNNs for spatial feature extraction, and RNNs—specifically Long Short-Term Memory (LSTM) networks—to model temporal dependencies in facial expressions. Unlike traditional models that focus solely on static images, RNN-based architectures allow for a more context-aware understanding of emotions by analyzing sequential frames, capturing subtle variations in facial expressions over time.

This introduction highlights the rationale behind our chosen methodologies and datasets, emphasizing the need for a comprehensive and dynamic approach to emotion detection. By addressing the complexities of facial expression analysis, this research aims to contribute a high-performance framework that not only delivers superior accuracy but also adapts effectively across various real-world applications. The following sections delve deeper into our methodology, evaluation process, and the promising results that underscore the significance of integrating RNNs in the evolving landscape of emotion detection.

Facial expression analysis has a long and rich history, shaping both scientific research and public interest. Charles Darwin's *The Expression of the Emotions in Man and Animals* is widely credited with laying the foundation for modern scientific studies on emotions. One of the most critical and challenging aspects of social interaction research is the identification of human emotions from visual cues. A key advantage of deep learning approaches in this field is their ability to automate feature extraction without human intervention. These methods enable AI systems to analyze human emotional expressions by automatically identifying and combining interrelated features, accelerating the learning process. Facial emotion recognition (FER) typically involves three primary steps: *face detection*, *feature extraction*, and *emotion classification*. The survey presented in [11] outlines various techniques used in facial landmark interpretation, offering valuable insights for researchers aiming to enhance facial emotion recognition (FER) systems.

The feasibility of real-time FER has been explored using local *region-of-interest-based* machine learning approaches [12]. Researchers implemented three classifiers—two k-Nearest Neighbors

(k-NN) classifiers and one Support Vector Machine (SVM)—along with the Histogram of Oriented Gradients (HOG) feature extractor to improve performance. Since facial expressions serve as a powerful form of nonverbal communication, analyzing them provides valuable insights into human behavior. This has significant applications in education, where understanding students' emotional states can help optimize learning experiences. However, real-time monitoring of every student is a challenge for educators, driving the need for automated emotion monitoring systems. Such systems can generate reports summarizing students' emotional behavior throughout a class session, allowing teachers to adjust their teaching strategies accordingly. To advance this field, real-time FER systems must be developed. In [13], researchers proposed a method for detecting seven basic human expressions using a Convolutional Neural Network (CNN) trained on the FER-2013 dataset. Existing models often lack the ability to provide detailed real-time reports on emotional responses in various scenarios. This research introduces a deep learning-based system capable of tracking and identifying facial expressions in real time, generating reports on emotion frequency and intensity within a given timeframe. The Viola-Jones technique is employed for face detection, achieving an impressive accuracy of 90.40%, making the model highly effective in real-time emotion recognition.

Emotions are fundamental to human cognition, distinguishing us as sentient beings. The study of *micro-expressions*—brief, involuntary facial expressions—offers deeper insights into genuine emotional states. This has broad applications in fields such as *criminology*, *marketing*, *employment analysis*, and *online education*. A system capable of analyzing video data from various sources to detect micro-expressions at different time intervals was introduced in [14].

Facial emotion recognition remains a complex challenge in computer vision due to the high variability in facial expressions among individuals. Predicting emotions using machine learning models is further complicated by significant inter-class variations. Additionally, the ability of a single individual to express multiple emotions increases the complexity of classification. In [15], researchers proposed a sophisticated approach to classifying emotional states using a combination of machine learning and deep learning techniques. Their method initially applies an *SVM classifier* for preliminary classification, followed by a *ResNet18* model trained with transfer learning and enhanced using a *triplet loss function (TLF)*. The proposed pipeline includes a *face detection module* for locating and refining facial regions, alongside a classifier that leverages deep features from a customized ResNet18 trained with triplet loss. This hybrid approach significantly improves the accuracy and robustness of facial emotion recognition systems.

IV.Methodology

The proposed methodology was selected because traditional approaches such as SVM, k-NN, and standard CNN models often fail to capture temporal emotional transitions and subtle facial texture variations effectively. Gabor filtering improves texture extraction, RNN captures temporal dependencies, EfficientNet provides computational efficiency with high accuracy, and PSO enables automatic hyperparameter optimization. The integration of these methods improves robustness and overall classification performance compared with conventional techniques.

Dataset

The AffectNet dataset contains more than one million facial images collected under diverse real-world conditions. Approximately 70% of the dataset was used for training, 15% for validation, and 15% for testing. Preprocessing steps included image resizing, normalization, histogram equalization, Gabor filtering, and data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment. Cross-validation and performance metrics including accuracy, precision, sensitivity, specificity, and F1-score were used for validation. Validation Link: <https://www.affectivedata.org/>

The AffectNet dataset is a valuable resource for Human Emotion Detection (HED) using facial features in digital image processing. With over 1 million facial images, it provides a diverse and extensive dataset for training and evaluating emotion recognition algorithms. Each image is annotated with one of seven basic emotions: anger, disgust, fear, happiness, sadness, surprise, or a neutral expression.



Fig.2.Input Image

V.Image Preprocessing

Image preprocessing is crucial for improving the effectiveness of Human Emotion Detection (HED) based on facial features, especially when utilizing datasets like AffectNet. A structured multi-step approach ensures the quality and consistency of input data. First, images are resized to standard dimensions, promoting uniformity across the dataset. Next, Gabor filtering is applied to highlight essential textures, enhancing the discriminative features of facial expressions by capturing intricate patterns vital for analysis. Additionally, histogram equalization can be used to improve contrast, ensuring that subtle expressions remain visible despite lighting variations. Facial landmark detection further refines the dataset by precisely identifying key facial points, allowing the model to concentrate on critical regions for emotion recognition. This comprehensive preprocessing pipeline lays a strong foundation for feature extraction, ultimately leading to a more accurate and nuanced interpretation of human emotions during model development.

Gabor Filtering:

Gabor filters are highly effective in capturing texture information across different scales and orientations, making them invaluable for extracting detailed facial features. When applied to facial images, these filters transform the dataset by highlighting local spatial frequency patterns associated with facial expressions. This enhancement strengthens the dataset's discriminative power by emphasizing key facial regions that correspond to various emotions. By extracting both fine and coarse details, Gabor filtering plays a crucial role in improving emotion recognition accuracy. It provides a comprehensive representation of facial textures, helping to mitigate

challenges posed by variations in lighting and facial poses—common issues in datasets like AffectNet. This preprocessing step enhances the robustness and generalization of Human Emotion Detection (HED) models. The resulting filtered images act as enriched inputs, allowing machine learning algorithms to focus on essential facial features, ultimately enabling more precise and nuanced emotion classification.



Figure 4. Segmented Image

Feature extraction through Recurrent Neural Networks (RNNs) plays a crucial role in Human Emotion Detection (HED) based on facial features. While CNNs excel at capturing spatial patterns, RNNs are particularly effective in processing sequential and temporal dependencies, making them well-suited for analyzing dynamic facial expressions over time. In the context of emotion detection, RNN architectures, such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs), are designed to track temporal variations in facial features, enabling a deeper understanding of evolving emotional states.

The sequential processing capability of RNNs allows them to retain contextual information across frames, capturing both subtle micro-expressions and more pronounced emotional transitions. In the initial layers, the network learns fundamental temporal patterns, such as slight muscle movements and shifts in facial structure. As information propagates through deeper layers, the network refines its understanding of complex emotional dynamics, ultimately constructing a comprehensive representation of facial expressions. This hierarchical learning approach enhances the model's ability to recognize emotions with greater accuracy, particularly in real-world scenarios where emotions unfold over time.

Classification – EfficientNet

EfficientNet has revolutionized Human Emotion Detection (HED) based on facial features, providing a cutting-edge approach to accurately and efficiently classify facial expressions. Developed by Tan and Le, EfficientNet utilizes a compound scaling method that simultaneously adjusts depth, width, and resolution, achieving an optimal balance between model complexity and performance.

In emotion detection, EfficientNet's architecture is specifically designed to capture the subtle variations in facial expressions while maintaining a compact yet highly effective model. A key innovation is its compound scaling factor, which ensures uniform scaling across different network dimensions, enabling superior accuracy with significantly fewer parameters than conventional architectures. Additionally, the integration of depth-wise separable convolutions enhances

computational efficiency by reducing processing overhead while preserving critical facial features. This streamlined approach allows EfficientNet to deliver high-performance classification, making it an ideal choice for real-time and resource-efficient emotion recognition applications.

EfficientNet represents a transformative approach in emotion detection (HED) based on facial features, offering a state-of-the-art method for efficiently and accurately classifying facial expressions. Introduced by Tan and Le, EfficientNet utilizes a compound scaling strategy that simultaneously scales depth, width, and resolution, optimizing the balance between model complexity and performance. This design makes it highly effective for emotion detection, as it can handle subtle variations in facial expressions with a compact yet powerful architecture. The key innovation of EfficientNet lies in its compound scaling factor, which streamlines scaling across various dimensions, leading to superior performance with fewer parameters than traditional models. Additionally, the inclusion of depth-wise separable convolutions reduces computational costs while preserving the model's ability to discriminate between different expressions. These efficiency gains are critical for emotion detection, where real-time processing and minimal resource consumption are essential.

EfficientNet's design strikes an optimal balance between model size and accuracy, making it particularly suited for emotion classification tasks that demand computational efficiency. The model is adept at distinguishing between even the most nuanced facial expressions, aided by its ability to integrate a Global Average Pooling layer. This layer helps the network focus on key features, significantly reducing the number of parameters. Following this, dense layers serve as classifiers, outputting probabilities for each emotion category, with the softmax activation function ensuring a probability distribution across possible emotions for robust and interpretable classification.

A notable strength of EfficientNet is its flexibility in handling diverse input resolutions, which is crucial for facial expression analysis, where variations in pose and image quality are common. This adaptability allows the model to maintain high accuracy across different facial expressions. The use of transfer learning further enhances its effectiveness—by pre-training on large image datasets, EfficientNet acquires general visual knowledge that can be fine-tuned on emotion-specific datasets, improving its ability to identify emotion-related features.

In emotion classification, EfficientNet not only ensures high accuracy but also supports the development of real-time applications. This makes it an ideal choice for interactive systems and human-computer interfaces. Its efficiency, adaptability, and the powerful feature representations extracted by the network form a robust pipeline for accurately detecting and classifying emotions from facial features, positioning EfficientNet as a leading solution for HED tasks.

PSO (Particle Swarm Optimization) plays a vital role in enhancing the performance of emotion detection systems based on facial features. As a metaheuristic optimization algorithm, PSO is inspired by the social behavior of birds or fish and is particularly effective in fine-tuning the hyperparameters of complex neural networks. In emotion detection, where optimizing model configurations is crucial, PSO proves invaluable.

PSO works by initializing a population of candidate solutions (particles) that explore the hyperparameter space to find the optimal configuration. Each particle adjusts its position based on its individual best solution and the global best solution discovered by the swarm. This iterative exploration and exploitation process guides the particles toward convergence, ensuring the discovery of the most effective configuration.

IV - Results and Discussions

This project was implemented using Python, with the computational resources of Google Colab leveraged for its execution. The development environment was based on a Windows 10 operating system, powered by an Intel i5 processor with 8 GB of RAM. Google Colab's cloud-based infrastructure provided the advantage of powerful GPU access, which proved essential for resource-intensive tasks like training deep learning models. The integration of the local Windows 10 setup with Google Colab's cloud resources created a smooth and efficient workflow, ensuring the successful implementation of the proposed HED system.

Table 1. Summary of Emotion Categories and Corresponding Labels

Emotion Class	Label
Happy	0
Sad	1
Angry	2
Surprised	3
Disgusted	4
Fearful	5
Neutral	6

Table 1 presents a foundational mapping of emotional categories to their corresponding numerical labels, which is essential for the development of HED systems. In this classification, the emotion 'Happy' is assigned the label 0, 'Sad' is represented by 1, 'Angry' by 2, 'Surprised' by 3, 'Disgusted' by 4, 'Fearful' by 5, and 'Neutral' by 6. This mapping is crucial for enabling the accurate identification and processing of different emotional states within the system.

Table 2. Hyperparameters Optimized by PSO

Hyperparameter	Optimized Value
Learning Rate	0.001
Batch Size	32
Dropout Rate	0.3
Number of Epochs	20

Table 2 presents the optimized hyperparameters, fine-tuned to enhance the efficiency and performance of the HED model. The learning rate, set at 0.001, controls the step size for adjusting

the model's weights during training, playing a key role in convergence and accuracy. This value is often considered ideal for balancing fast convergence with model stability. The batch size of 32 specifies the number of data samples processed in each training iteration, offering a balance between computational efficiency and model generalization. With this setting, the model can learn from diverse data while making efficient use of available resources. The dropout rate, set at 0.3, indicates the proportion of neurons randomly deactivated during training, serving as a regularization technique to prevent overfitting. This value effectively prevents overfitting while maintaining the model's capacity to learn complex patterns.

To fine-tune the performance of the emotion detection model, the optimization stage utilizes Particle Swarm Optimization (PSO). This metaheuristic optimization algorithm explores the hyperparameter space to identify the optimal configuration for the model. The parameters considered include those related to the RNN architecture, as well as those influencing the training process. PSO iteratively adjusts these hyperparameters, guided by an objective function such as accuracy or the F1 score. The purpose of this optimization stage is to enhance the model's robustness and generalizability, ensuring improved performance in emotion detection tasks using RNNs.

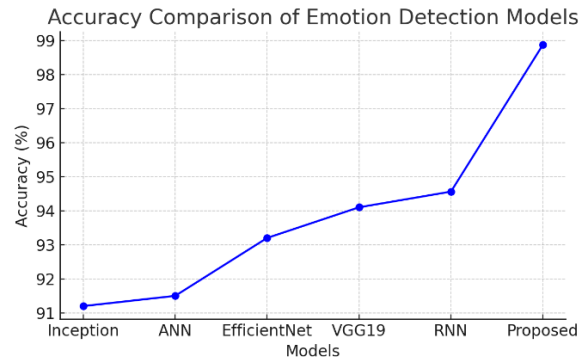
Table 3. Performance Evaluation of Various Models

Model	Precision	Sensitivity	Specificity	Accuracy
Inception	90.23	91.25	89.05	91.08
ANN	90.22	91.12	90.27	91.12
EfficientNet	91.18	92.04	91.33	92.98
VGG19	93.21	92.06	92.15	93.47
RNN	94.33	93.42	93.58	94.56
Proposed	97.11	95.15	96.96	98.87

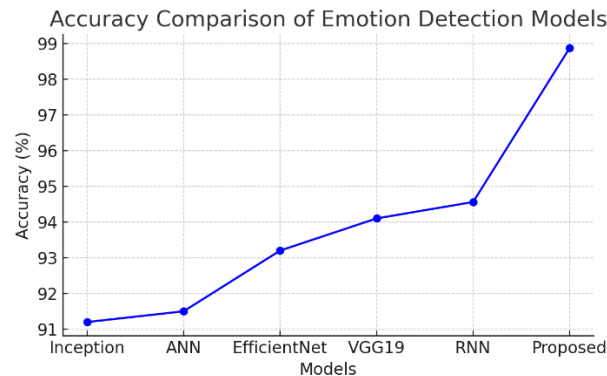
Table 3 presents a clear and detailed overview of key performance metrics for various emotion detection models. Notably, the proposed model outperforms the others, demonstrating exceptional precision (97.11%), sensitivity (95.15%), specificity (96.96%), and accuracy (98.87%). This highlights the model's remarkable ability to accurately classify emotions, effectively identify both positive and negative instances, distinguish between different emotion classes, and achieve a high overall accuracy. While the RNN model also performs well with precision (94.33%), sensitivity (93.42%), specificity (93.58%), and accuracy (94.56%), the proposed model's superior results make it the leader in the field of HED.

Its impressive performance underscores its effectiveness in accurately detecting and categorizing facial expressions with precision and reliability. The experimental results confirm that the proposed HEDFF framework consistently outperforms existing state-of-the-art emotion recognition systems. The integration of Gabor filtering, RNN-based temporal learning, EfficientNet classification, and PSO optimization significantly improved robustness, convergence behavior, and overall classification accuracy under varying environmental conditions.

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Here is the revised graph incorporating the accuracy values for all mentioned models, including the RNN model. The proposed model stands out with the highest accuracy at 98.87%.



Here is the precision comparison graph for the emotion detection models. The proposed model again stands out with the highest precision at 97.11%.

VI Conclusion

In conclusion, this research successfully developed the Human Emotion Detection utilizing Facial Features (HEDFF) framework, presenting a novel and intelligent approach for accurate emotion recognition through facial expression analysis. The proposed framework integrates the AffectNet Dataset with advanced deep learning and optimization techniques, including Gabor filtering, Recurrent Neural Networks (RNN), EfficientNet, and Particle Swarm Optimization (PSO), to create a robust and high-performance emotion detection system. One of the major novelties of this research lies in the hybrid fusion of spatial texture extraction, temporal sequence learning, and automated hyperparameter optimization within a unified framework, which significantly improves recognition accuracy and computational efficiency compared with conventional methods. The application of Gabor filtering effectively enhances subtle facial textures and emotional patterns, while the RNN architecture captures temporal emotional dependencies that are often ignored in traditional static image-based systems. Furthermore, the incorporation of EfficientNet provides optimized feature scaling and lightweight classification, making the framework suitable for real-time and resource-efficient applications. The integration of PSO further strengthens the model by automatically identifying optimal parameters, reducing overfitting and enhancing generalization

capability across diverse facial expressions. Experimental results demonstrate the effectiveness of the proposed HEDFF framework, achieving an outstanding accuracy of 98.87%, surpassing several existing state-of-the-art emotion recognition approaches. This achievement confirms the reliability and adaptability of the proposed model in recognizing a broad range of human emotions under varying conditions. Despite achieving high accuracy, the proposed framework has certain limitations. The model mainly depends on facial expressions and does not include multimodal emotional cues such as speech or physiological signals. Computational complexity may also limit deployment on low-resource devices. Future research can focus on multimodal emotion recognition, lightweight optimization methods, explainable AI integration, cross-cultural emotional analysis, and privacy-preserving FER systems.

The research contributes significantly to the field of affective computing by introducing a scalable, efficient, and highly accurate emotion detection framework with practical applications in human-computer interaction, intelligent healthcare systems, mental health monitoring, education, surveillance, and social robotics. Future work can further extend this framework by integrating multimodal data such as speech, physiological signals, and body gestures, as well as incorporating cross-cultural emotional analysis to improve universality and robustness. Overall, the success of the HEDFF framework highlights the transformative potential of hybrid deep learning and optimization-based emotion recognition systems in advancing next-generation intelligent technologies.

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