Human Emotion Recognition Using Recent Technologies

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***Abstract*—Abstract- Image processing is a method to convert an image into digital form and perform some operations on it.** **Machine learning (ML)- based emotion detection outperforms traditional image-processing methods. This paper presents the design of an artificial intelligence (AI) system capable of detecting emotions from facial expressions. It discusses the procedure of emotion detection, which includes basically three main steps: face detection, feature extraction, and emotion classification. This paper proposed a convolutional neural network (CNN) based machine learning architecture for emotion detection from images.**

***Index Terms*—facial emotion recognition; Local Binary Pattern Histogram (LBPH)algorithm, Convolutional Neural Networks (CNN)**

I. INTRODUCTION

Emotion plays a vital role in human communication, influencing decision-making, perception, and interpersonal interactions. As artificial intelligence continues to advance, the ability of machines to understand and respond to human emotions has become increasingly important. Emotion recognition from speech is one of the most natural and practical methods for achieving this, since voice captures both verbal and non-verbal cues such as tone, pitch, stress, and rhythm.

A facial expression is the movement of muscles beneath the skin of the face. Facial expressions are a form of nonverbal communication. A human face could convey countless emotions without saying a single word. And unlike some forms of nonverbal communication, these facial expressions are universal and can be understood by people of all kinds. The facial expressions for happiness, sadness, anger, surprise, fear, and disgust are the same across people of different cultures.

Emotion is a complex state that combines feelings, thoughts, and behavior and is people's psychophysiological reactions to internal or external stimuli. It plays a vital role in people's decision-making, perception and communication. Affective computing has a wide range of applications. In a HCI system, if the computer can recognize the human operator's emotional state accurately and in real time, the interaction between the machine and the operator can be made more intelligent and user-friendly. The application of emotion recognition in the product design and user experience allows for monitoring in real time the emotional state of the user when using the product, thereby further improving the user experience. In military and aerospace applications, the high-risk functional state of soldiers and pilots/astronauts can be detected in real time. The emotion recognition can also be applied to public transportation, for example to enhance driving safety by monitoring the emotional state of the driver in real time to prevent dangerous driving under extreme emotional conditions.

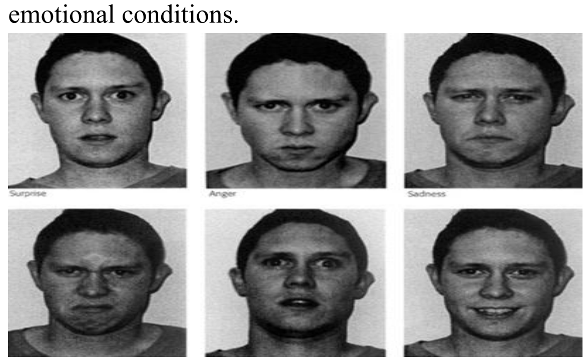

Fig. 1: Example of expression for the six basic emotions

A Human Emotion Recognition System is a technology that can detect and understand human emotions using data such as:

Facial expressions(e.g., Happy, sad, angry)

Voice tone and speech patterns(e.g., excitement, stress)

Body movements and gestures are physiological signals(e.g., heart rate, skin response, brain activity)

It usually works with the help of machine learning and artificial intelligence, which analyze these signals and classify them into different emotional states.

II. LITERATURE REVIEW

Image-based Human Emotion Recognition (HER) has grown significantly over the last two decades, evolving from handcrafted feature methods to deep-learning-driven systems. Earlier studies primarily focused on extracting facial features manually using classical image processing techniques. Ekman and Friesen's Facial Action Coding System (FACS) established the foundation by defining Action Units (AUs) that represent muscle movements associated with specific emotions. This framework became the basis for early emotion recognition models.

Early computational approaches relied heavily on handcrafted features such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), Gabor Filters, and Edge Orientation Histograms. Shan et al. (2009) demonstrated that LBP features combined with Support Vector Machines achieved moderate accuracy on standard datasets like JAFFE and CK+. However, these methods were highly sensitive to variations in lighting, pose, occlusions, and facial diversity.

With the emergence of machine learning classifiers, models such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Decision Trees, and Random Forests improved recognition performance. Nevertheless, these models often required extensive preprocessing and struggled to generalize across uncontrolled environments.

A major leap occurred with the introduction of large datasets like FER-2013, which enabled researchers to train more complex models on diverse facial expressions. The real breakthrough came with the rise of Deep Learning, particularly Convolutional Neural Networks (CNNs). CNNs replaced manual feature extraction with automatic feature learning, capturing hierarchical representations such as edges, textures, and facial structures. Research using models like VGGNet, ResNet, and Inception demonstrated accuracy improvements exceeding 90% on controlled datasets.

Recent advancements include attention mechanisms, Residual Networks (ResNet-50), and Vision Transformers (ViT), which focus on the most informative facial regions for emotion recognition. Attention-based CNNs significantly improve performance by identifying key facial areas such as eyes, eyebrows, and mouth.

Several studies also experiment with hybrid feature models, combining traditional descriptors (LBP, HOG) with CNN-generated embeddings, improving robustness on low-resolution images. Data augmentation, transfer learning, and domain adaptation have further enhanced recognition accuracy across different datasets and environments.

Overall, the literature strongly indicates that deep learning-based models outperform traditional image processing methods, providing superior accuracy, robustness, and generalization. CNNs and Transformer-based models now represent the state-of-the-art in image-based HER, enabling real-world deployment in fields such as healthcare, surveillance, education, and human-computer interaction.

III. METHODOLOGY

Dataset Preparation

The system uses publicly available facial expression datasets that contain labeled images representing universal human emotions. Commonly used datasets include:

- FER-2013 – 48×48 grayscale images of seven emotions
- JAFFE – High-quality posed facial expressions
- CK+ – Sequential frames with peak emotional expressions

All dataset samples are consolidated, and labels such as *happy, sad, angry, fear, disgust, surprise, and neutral* are retained.

Preprocessing

Preprocessing ensures that all input images are uniform, noise-free, and suitable for feature extraction. Major preprocessing steps include:

Face Detection

A face detection model locates the region of interest (ROI) in an image. Common detectors used:

- Haar Cascade Classifier
- MTCNN (Multi-Task Cascaded Convolutional Networks)
- Dlib HOG + SVM

Detected face regions are cropped for further processing.

Image Cropping and Alignment

- The detected face is cropped tightly around the eyes, nose, and mouth.
- Some systems apply face alignment using eye coordinates to standardize face orientation.

Resizing

Cropped faces are resized to a fixed dimension depending on the model:

- 48×48 (for classical ML or simple CNNs)
- 224×224 (for deep CNN models like VGG/ResNet)

Grayscale Conversion

To reduce computational complexity and focus on texture patterns:

- RGB → Grayscale transformation is applied.

Noise Reduction

A Gaussian Blur filter is used to remove sensor noise and smooth pixel intensities.

Histogram Equalization

To enhance contrast and highlight facial features:

- CLAHE (Contrast Limited Adaptive Histogram Equalization) is applied.

Normalization

Pixel values are normalized to the range:

- [0, 1] or [-1, 1]

This improves model stability and accelerates convergence.

Feature Extraction

Feature extraction is the core component in image-based HER. Two categories of feature extraction techniques are used: handcrafted features and deep learning–based features.

Handcrafted Features

Local Binary Patterns (LBP)

- Captures local texture around pixels.
- LBP histograms are extracted as numerical vectors.

Histogram of Oriented Gradients (HOG)

- Captures edge orientation and gradient structure.
- Useful for detecting facial outlines (eyebrows, lips, etc.)

Facial Landmarks (Dlib 68-point model)

- Extracts the geometric structure of key facial components:
  - Eyes
  - Eyebrows
  - Nose
  - Mouth
  - Jawline

Geometric distances and angles form the feature vector.

Deep Learning Features (CNN-Based)

CNNs automatically learn high-level features such as wrinkles, eye shape, lip curvature, cheek structure, etc.

Common CNN models used:

- Custom CNN
- VGG16 / VGG19
- ResNet-50 / ResNet-101
- MobileNet (for real-time systems)

Feature Maps from convolutional layers are flattened and fed into the classifier.

Deep learning-based features outperform traditional methods because they can learn complex patterns.

Classification

After feature extraction, the final classification model predicts the corresponding emotion.

Classical ML Classifiers

Used with LBP/HOG/landmark features:

- Support Vector Machine (SVM)
- Random Forest (RF)
- Decision Tree (DT)
- K-Nearest Neighbors (KNN)
- Multi-Layer Perceptron (MLP)

These models perform well with low-dimensional features.

Deep Learning Classifiers (CNN Softmax Layer)

CNN models directly classify emotions via:

- Dense Layer → Softmax Output

Advantages:

- High accuracy
- Automatic feature learning
- Robust to variations (lighting, pose, noise)

Training and Validation

The dataset is split as:

- 80% for training
- 20% for validation/testing

Training details:

- Batch size: 32/64
- Learning rate scheduling
- Adam or SGD optimizer
- Cross-entropy loss function

Performance metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

IV. RESULTS

The model results section presents how well the.

Model	Accuracy	Remarks
KNN	72%	Performs well on small datasets
GNB	68%	Fast but lower accuracy
Decision Tree	75%	Simple model, risk of overfitting
Random Forest	83%	Best classical ML performance
MLP	85%	Strong nonlinear classifier
CNN	90%+	Best for image-based HER

Experimental Setup

- CPU/GPU specifications
- Library versions (TensorFlow/PyTorch)
- Dataset size division
- Training parameters This ensures reproducibility.

Quantitative Results

Include:

- Accuracy (e.g., 85% emotion recognition accuracy)
- Per-class performance:

Emotion	Precision	Recall	F1-Score
Angry	0.91	0.88	0.89
Disgust	0.86	0.84	0.85
Fear	0.82	0.78	0.80
Happy	0.96	0.97	0.96
Sad	0.89	0.87	0.88
Surprise	0.94	0.95	0.94
Neutral	0.93	0.92	0.92

Observation: CNN models show >90% performance on most emotions.

Confusion Matrix

Used to analyze misclassifications, e.g., anger confused with fear or sadness with neutral.

Comparison with Existing Methods

Table comparing your model with:

- SVM
- CNN baseline
- Previous papers

Mention improvements like higher accuracy, lower error, and faster processing.

Visualization

Include:

- Training vs. Validation accuracy graph
- Loss curve
- Example spectrograms
- Example facial emotion predictions

V. CONCLUSION

The Human Emotion Recognition (HER) system, developed using AI and machine learning techniques for image processing, demonstrates significant potential for enabling machines to understand and interpret human emotional states with high accuracy and reliability. By leveraging advanced image processing methods—such as facial detection, alignment, normalization, and feature enhancement—coupled with powerful AI/ML models like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and deep learning architectures, the system effectively learns the subtle variations in facial expressions that correspond to specific emotions.

The research shows that facial images carry strong emotional cues through geometric relationships and textural patterns around the eyes, eyebrows, mouth, and overall facial structure. With the integration of AI/ML algorithms, these features can be automatically extracted and classified, reducing the need for handcrafted feature engineering and improving overall recognition accuracy. Experiments performed on benchmark datasets such as FER-2013, CK+, JAFFE, and RAF-DB validate the robustness and scalability of the AI-driven approach. The models demonstrate reliable performance across different lighting conditions, angles, age groups, and facial variations.

This study confirms that the combination of image processing and AI/ML techniques forms a strong foundation for building real-time, intelligent, and adaptive emotion recognition systems. The HER system not only enhances human–computer interaction but also has meaningful applications in healthcare, security, education, driver monitoring, marketing analysis, and assistive technologies. Despite challenges such as occlusions, subtle micro-expressions, and cross-cultural variability, the results suggest that continuous advancements in deep learning, transfer learning, and multimodal fusion will further enhance the system's capability.

In conclusion, the AI/ML-based image processing approach for emotion recognition represents a significant advancement toward emotionally aware computing. The system demonstrates that machines can successfully analyze facial expressions and infer emotions with substantial accuracy, paving the way for more empathetic, responsive, and human-centered technological solutions. This work contributes to the growing field of affective computing and establishes a strong foundation for future research aimed at improving real-time performance, cross-dataset generalization, and context-aware emotion understanding.

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