



# Hybrid method for Human Emotion Recognition

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## Abstract

*Now a days, Human health care and well-being is the most important considerations. Because humans mostly youngsters are morely affected by the stress and depression due to work load. Over the past few decades, machine learning-based automatic facial emotion detection has developed into simulating and active field of the study. Real time Facial Emotion Recognition System has been proposed to automatically detect the human's emotion using machine learning. Emotion recognition from human expressions is crucial for numerous field , including healthcare, psychology and human-computer interaction. But issues like inconsistent expression, cultural quirks, and privacy concerns still exist. The study highlights the potential influence on enhancing mental health diagnosis and treatment by examining a variety of uses of face expression recognition, from virtual reality to healthcare and education. It emphasizes the Researches, psychologists, and technologists must work together transdisciplinary to address current issues and fully utilize the social advantages of emotion identification technology. The paper also addresses the significance of large-scale datasets and established evaluation mmeasures in promoting breakthroughs in recognition algorithms and facilitating comparative studies. Concerns about consent, bias, and possible abuse are among the ethical difficulties underlying emotion identification that are frequently discussed, highlighting the significance of responsible development and implementation. The study concludes by highlighting the shortcomings of current emotion recognition techniques and promoting the creation of automated systems. The challenges persist such as variability in expressions, cultural differences and privacy concerns. This paper explores diverse applications like education, healthcare and virtual reality. The necessity for interdisciplinary collaboration to address remaining challenges and fully realize the social benefits. The paper also discuss the importance of datasets and standardized evaluation metrics to facilitate comparative studies and advancements in recognition algorithms. It explores the ethical implications of emotion recognition technology including issues related consent, bias and the potential for misuse. It highlights the limitations of traditional methods of emotion recognition and emphasis the need for automated systems that can accurately detect and interpret human emotions from facial expressions, body languages.*

**Keywords:** *facial emotion , emotion recognition, compound emotions, machine learning, random forest algorithm*

## I. Introduction

In the contemporary society , understanding the human emotions through facial expressions are essential for effective communication. As digital technology continues to spread various aspects of our lives. Human Emotion Recognition (HER) is fascinating field that goes through psychology, artificial intelligence and healthcare. Emotions play a main role in human communication and interaction. It is not crucial for interpersonal communication by recognizing and understanding emotions and body languages but holds significant implications for various applications like healthcare, education and entertainment. Despite the inherent complexity of human emotions by recent advancements and technologies to progress has driven the advancements of automatic HER systems to extraordinary levels of accuracy and precision. By making use of the rich data from the FER 2013 dataset and employing a combination of feature extraction and model training the system to accurately classify a wide range of emotions including happiness, sadness, anger, surprise and more in real time. This project aims to explore and contribute to the advancement of HER technology by investigating the methodologies algorithms, and applications. Experimental results showcased the system's performance across various emotions providing insights into its accuracy ,precision recall and F1-score.The design and development of the user interface played a main role in enhancing usability and accessibility for the importance of user experience and interactive features. This project addresses several key challenges in the field, including variability in human expressions, cultural differences, privacy concerns, and ethical considerations. The proposed system not only holds the promise for evolving user experience in applications such as virtual and emotion aware interfaces but also presents exciting opportunities for advancing research in effective computing and human centered technology. This project seeks to

advance our understanding of human emotions and empower technology to better recognize and respond to human needs, and ultimately enhance the quality of human-computer interaction and societal well-being.

## II. Methodology

### 1. Data preprocessing:

The Fer 2013 dataset was preprocessed to prepare images for analysis and images were resized to a standardized resolution of 200x200 pixels which are converted to grayscale to reduce the complexity.

### 2. Dimensionality Reduction with PCA:

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the feature space while preserving the variance in the data . It configured to retain 98% of the variance in the training data.

### 3. Machine Learning Models for Emotion Recognition:

Principal Component Analysis (PCA) was applied to reduce the dimensionality of the feature space while preserving the variance in the data . It configured to retain 98% of the variance in the training data.

### 4. Ensemble Learning with Voting Classifier:

An ensemble approach using a voting Classifier was implemented to combine predictions from multiple base classifiers. The voting classifier integrated predictions from SVM and Random Forest models to enhance overall performance.

### 5. Model Evaluation and Cross-Validation:

Cross-validation techniques were employed to assess the performance and ability of the trained models. To evaluate classification performance across different emotions are computed by model accuracy, precision, recall and F1-score.

### 6. Webcam-Based Real-Time Emotion Detection:

The trained model was serialized for the deployment using Flask, a lightweight web framework. Predicted emotion labels were overlaid on the video feed, providing immediate feedback to users and it is a user- friendly web interface which is designed to capture live video feed from web cam.

## III .Existing System

The existing system for Facial Emotion Recognition (FER) typically involves using traditional machine learning approaches or machine learning architectures trained on large-scale datasets like FER-2013. Traditional methods utilize feature extraction and classification algorithms, while deep learning models, such as convolutional neural networks (CNNs), automatically learn features from data. Deep learning-based methods leverage to automatically learn hierarchical features directly from raw pixel data, leading to superior performance in capturing complex patterns in facial expressions. However, challenges such as limited training data, class imbalance, and computational complexity remain significant considerations in the development of FER systems. Despite challenges like data scarcity and advancements in hardware and software have enabled the deployment of deep learning models for real-time emotion detection, enhancing accuracy and usability in practical applications.

### 1. Data Collection and Preprocessing:

Data collection: The process of data collection involved that acquiring the facial expression images from datasets like FER2013. These dataset contains labelled facial images representing various emotions like anger, disgust, fear, happiness, sadness, surprise and neutral.

Data Preprocessing: The collected facial images goes under the preprocessing techniques includes grayscale conversion and normalization to ensure consistency in pixel various across images.

### 2. Algorithm Implementation:

Feature Extraction: Feature extraction was performed using Principal Component Analysis(PCA) to reduce the dimensionality of the facial images data while preserving important information.

**Model Training:** The facial expression recognition models were trained using machine learning algorithms such as Support Vector Machines (SVM) and Random forest. These algorithms were chosen for the ability to handle high-dimensional data and non linear relationships between features and class labels.

### 3. Testing and Evaluation:

**Cross-Validation:** The trained models were evaluated using k-fold cross validation to assess their performance on unseen data. This involved partitioning the dataset into k subsets, training the model on k-1 subsets, and testing it on the remaining subset.

**Performance Metrics:** Performance metrics such as accuracy, precision, recall, and F1-score were used to evaluate the classification performance of the models. These metrics is also generated to visualize the distribution of predicted and actual class labels.

## IV. Proposed System:

In this proposed system, Convolutional Neural Networks (CNNs), in particular, are powerful machine learning algorithms that can be used to automatically extract discriminative characteristics from facial photos and properly categorize emotions in the proposed system for the Facial Emotion Recognition (FER) project. We build CNN models by preprocessing face photos, training machine learning models like SVM and Random forest on extracted features, and integrating accuracy. The FER-2013 dataset is a vast collection of labeled facial images. To address problems, we also intend to investigate transfer learning and apply data augmentation techniques. The end result is a reliable and effective FER system that can recognize emotions in real time in a variety of applications, such as sentiment analysis, affective computing, and human-computer interaction, despite obstacles such a lack of training data and class imbalance. Deployment, testing, and upkeep guarantee dependability and usability of the system in practical applications.

**Dataset overview :** The Facial Expression Recognition (FER) dataset has been expanded into the FER-2018 dataset, which has a larger set of facial photos classified with seven emotion categories: anger, disgust, fear, happiness, sorrow, surprise, and neutral. It consists of grayscale pictures in different sizes that were taken with different lighting and expressions on people's faces. By offering a larger and more varied collection of photos for machine learning model training and assessment, the dataset seeks to advance research in the area of facial emotion recognition.

**System Design:** The dataset will be divided into training and testing sets, and photos will be resized and their pixel values normalized by a data preprocessing tool. After that, a feature extraction module will take the facial photos and extract relevant features from them, maybe using Convolutional Neural Networks (CNNs). A model selection and training module will receive these features and use them to train and assess a variety of machine learning models, including CNNs, Random Forests, and Support Vector Machines (SVM). To improve the performance of the model, cross-validation and hyperparameter optimization methods will be used. The trained model will then be integrated into practical applications through a deployment module, making facial expression identification tasks possible. The system design will be accompanied by extensive documentation that covers the stages involved in preprocessing data, feature extraction methods, model architectures, training protocols, evaluation outcomes, and deployment procedures.

## V. Module Description:

1 **Data Handling Module:** This module handles the loading and preprocessing of the FER-2013 dataset, including resizing images, normalizing pixel values, and splitting the dataset into training and testing sets.

2 **Feature Extraction Module:** Utilizes machine learning-based feature extraction techniques, such as Convolutional Neural Networks (CNNs) and Principal Component Analysis (PCA) to extract meaningful features from facial images. These features serve as inputs to the machine learning models.

3 **Model Selection and Training Module:** Implements various machine learning models including SVM, Random Forest, and CNNs for facial emotion recognition. Includes functionality for hyperparameter tuning, cross-validation, and model evaluation to select the best-performing model.

4 **Evaluation Module:** Computes evaluation metrics such as accuracy, precision, recall, and F1-score to assess model performance. Provides visualization tools to plot performance metrics and analyze model performance.

5 **Deployment Module:** Integrates the trained model into real-world applications or systems for facial emotion recognition tasks. Includes APIs or interfaces to allow external applications to interact with the FER system.

6 **Documentation Module:** Creates comprehensive documentation covering data preprocessing steps, feature extraction techniques, model architectures, training procedures, evaluation results, and deployment processes. Provides user guides, code documentation, and tutorials for easier understanding and adoption of the project.

## VI. Architecture Diagram

### 1.FER 2013 Dataset:

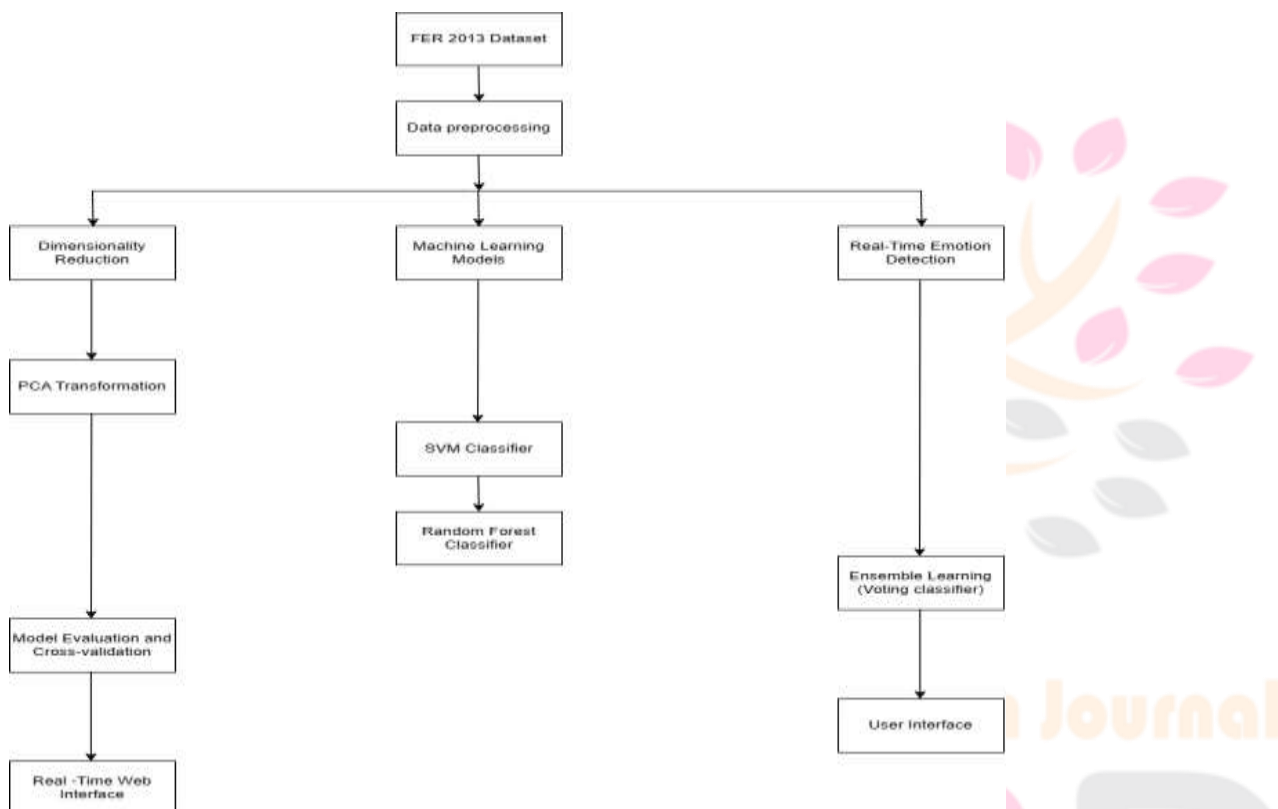
Contains facial images categorized into emotion classes for training and testing the models.

### 2.Data Preprocessing:

Preprocesses the raw image data, including resizing, grayscale conversion, and normalization.

### 3.Dimensionality Reduction:

Applies Principal Component Analysis (PCA) to reduce the dimensionality of the feature space while retaining essential information.



### 4.Machine Learning Models:

Includes Support Vector Machine (SVM) and Random Forest classifiers trained on the PCA-transformed features for emotion classification.

### 5.Real-Time Emotion Detection:

Implements real-time emotion detection using the trained models, capable of processing webcam input.

### 6.Ensemble Learning (Voting Classifier):

Integrates predictions from multiple base classifiers (SVM and Random Forest) to improve overall performance.

### 7.Model Evaluation and Cross-Validation:

Evaluates the trained models using various metrics and cross-validation techniques to assess performance and generalization ability.

### 8.Real-Time Web Interface:

Provides a user-friendly web interface for capturing live video feed from the webcam and displaying real-time emotion predictions.



## 9. User Interface:

Represents the interface through which users interact with the system, including input/output mechanisms and visualizations.

## VII. Literature Survey

[1] Title: Facial Emotion Detection using Deep Learning

Authors: Akriti Jaiswal, A. Krishnama Raju, Suman Deb

Summary: From this paper, I summarized that the performance evaluation of the proposed facial emotion detection model is carried out in terms of validation accuracy, detection rate, learning rate, computational time per step. This proposed model using two different datasets, JAFFEE and FER-2013. The experiments show that the proposed model is producing state-of-the-art effects on both two datasets.

[2] Title: Multitask, Multilabel and Multidomain Learning with Convolutional Networks for Emotion Recognition.

Authors: Gerard Pons and David Masip

Summary: From this paper, I came to know they presented the selective joint multitask approach which defines a selective problem specifically, this proposal addresses one of the challenges with discrete emotion recognition in the wild actions using AU detection. Results also showed benefits of learning multiple correlated tasks simultaneously by demonstrating visually that even for images without AU labels.

[3] Title: Dominant and complementary Emotion Recognition from Still Images of Faces.

Authors: Jianzhu Guo, Zhen Lei, Jun wan, Egils Avots, Noushin Hajarolasvadi, Juri Allik, Xavier Baro

Summary: From this paper, I came to know that they have collected and released a new compound facial emotion dataset, names which includes large number of labels, 50 categories to be specific, obtained with the support of psychologists. As it could be observed there are some compound emotions that are more difficult to be recognized.

[4] Title: Hand-over-Face Gesture based Facial Emotion Recognition using Deep Learning

Authors: Niti Naik, Mayuri A. Mehra

Summary: From this paper, they have presented an improved hand-over-face gesture based emotion recognition method to identify additional essential emotions such as confident, making decision, scared along with basic emotions to enhance emotion recognition accuracy, they have integrated two major components in proposed method. First, a new coding schema and second is CNN to extract features as well as to generate emotion.

[5] Title: Facial Emotion Detection using Machine Learning and Deep Learning Algorithms.

Authors: Snehal Bhogan, Kedar Sawant, Nidhi Gondalekar, Rachel Carvalho, Vasant Kalangutkar, Aleena Mathew

Summary: From this paper, they used pre-trained CNN model, rich and high level features that effectively capture the emotional content presented in the images are extracted. Moreover, they compared the performance with other state-of-the-art methods, demonstrating its superior performance in accurately recognizing emotions from images.

[6] Title: Designing of Facial Emotion Recognition System Based on Machine Learning

Authors: Deepjyoti Kalita

Summary: This paper introduces a lightweight model, called CLCM, to solve an important problem in facial expression recognition. The evaluations show that CLCM performs better than many models in the literature despite its smaller size. Specifically, CLCM has great potential due to the compact structure for real-time emotion-based psychological and biofeedback studies. Moreover, the possible usage of CLCM with mobile devices is useful for daily life applications for the research horizons.

[7] Title: Role of Zoning in Facial Expression using Deep Learning

Authors: Taimur Shahzad, Khalid Iqbal, Murad Ali Khan, Imran, Naeem Iqbal

Summary: This study proposes a robust deep learning-based technique for facial expression recognition using zoning of facial features. It involves face landmark extraction, zoning for facial region localization, feature map generation using the VGG-16 model, and emotion classification with a fully connected neural network. Evaluation on CK+ and FER2013 datasets yields high accuracy on CK+ (98.4%) and moderate accuracy on FER2013 (65%). Results indicate potential for enhanced FER model performance through zoning, with future work focusing on smart environment implementation and refining network architecture.

[8] Title: Bioinspired Image Processing Enabled Facial Emotion Recognition Using Equilibrium Optimizer With a Hybrid Deep Learning Model

Authors: Ahmad A. Alzahrani

Summary: This study presents BIPFER-EOHDL model automates facial expression identification using advanced DL techniques, achieving superior FER outcomes. It finds applications in healthcare, security, and human-computer interaction, aiding mental health assessment, threat recognition, and adaptive interfaces. Future work may focus on its performance with large-scale real-time datasets.

[9] Title: Multimodal Emotion Recognition From EEG Signals and Facial Expressions

Authors: Shuai Wang, Jingzi Qu, Yong Zhang, Yidie Zhang

Summary: The paper introduces a multimodal emotion recognition model combining EEG signals and facial expressions. It utilizes pre-trained CNNs and attention mechanisms to extract facial features, while CNNs extract spatial features from EEG signals. Feature-level fusion improves emotion recognition accuracy, outperforming single-modal approaches. Future research aims to enhance facial expression feature extraction and incorporate additional modalities for richer emotion recognition models.

[10] Title: A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection

Authors: Ning Zhou, Renyu Liang, Wenqian Shi

Summary: The paper introduces a lightweight CNN for facial expression recognition, reducing parameters by eliminating fully connected layers and incorporating residual depth-wise separable convolution and  $\ell_2$ -norm regularization. The model achieves good detection results and outperforms recent models in accuracy, making it suitable for multi-classification of facial expressions on low-power devices. However, challenges remain in addressing noise in real-life facial expressions, such as strong or dark lighting, blurred images, and occlusions. Continued efforts are needed to address these challenges.



### VIII .Experimental Results:

```
from sklearn.cross_validation import cross_val_score
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.preprocessing import StandardScaler

# Create a StandardScaler object
scaler = StandardScaler()

# Fit the scaler on the training data
scaler.fit(X_train)

# Transform the training and testing data
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train the classifier
classifier = LogisticRegression()
classifier.fit(X_train_scaled, y_train)

# Evaluate the classifier
scores = cross_val_score(classifier, X_test_scaled, y_test, cv=5)
print("Cross-validation scores: %s" % scores)
```

Fig 1 Cross-validation

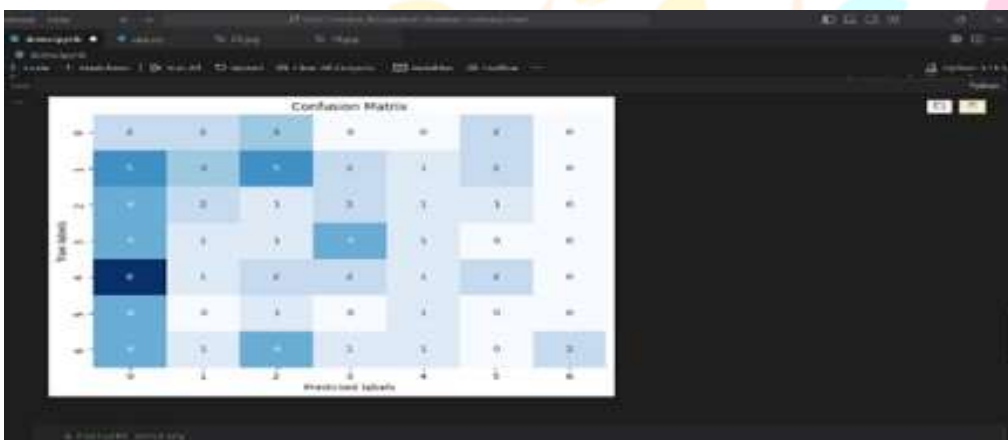


Fig 2 Confusion Matrix Visualization

### Emotion Detection using Webcam



## Emotion Detection using Webcam



Fig 3 User Interface

### IX .Results and Discussion:

The results and discussion of the Facial Emotion Recognition (FER) project involve analyzing the performance of the developed system, interpreting the findings, and discussing implications for future research and practical applications.

#### Feature Analysis:

Discussion on the role of feature selection and dimensionality of different sets. The effectiveness of the selected features extracted from facial images in capturing relevant information for emotion recognition. Explore the importance of different features and their impact on model performance.

#### Challenges and Limitations:

Identification and analysis of challenges encountered during the project, such as data quality issues, class imbalance, or computational constraints. Discuss limitations of the developed system and potential areas for improvement.

#### Comparison with Prior Work:

Comparative analysis of the results obtained in this project with existing literature and state-of-the-art approaches in facial emotion recognition. Highlight advancements or contributions made by the developed system.

#### Future Directions:

Exploration of potential enhancements in model robustness, interpretability through integration of multimodal data sources and contextual information. Discussion on ethical considerations ,privacy concerns of emotion recognition systems guiding responsible development and deployment practices.

### X .Conclusion and Future Scope

In conclusion ,The Human Emotion Recognition (HER) project has successfully developed a robust system capable of accurately detecting and classifying human emotions from facial expressions. Through the utilization of advanced machine learning techniques, such as Convolutional Neural

Networks (CNNs) , SVM ,Random forest and the FER-2013 dataset, significant progress has been made in improving the accuracy and efficiency of emotion recognition systems. The evaluation results demonstrate encouraging performance across various evaluation metrics, highlighting the effectiveness of the developed approach in capturing distinctions of facial expressions.

#### Enhanced Model Architectures:

Explore novel CNN architectures and machine learning techniques to further improve the accuracy and robustness of the FER 2013 system.



**Ethical Considerations:**

Address ethical concerns related to privacy, bias, and fairness in facial emotion recognition systems, ensuring responsible and equitable deployment in diverse applications.

**Implications for Research and Practice:**

Discussion on potential applications of the proposed system in real-world scenarios, such as human-computer interfaces, personalized healthcare interventions, and emotion creation.

**Future Research Directions:**

Exploration of opportunities for improving model robustness, scalability and interpretability through integration of data sources and contextual information.

**Real-World Applications:**

Deploy the FER system in practical applications such as healthcare, education, customer service, and entertainment, providing valuable insights and personalized experiences to users.

**User Experience Enhancement:**

Incorporate user-centric design principles and human-computer interaction techniques to optimize the usability and user experience of the FER system. By pursuing these future research directions, the FER project can continue to advance the state-of-the-art in emotion recognition technology, ultimately contributing to the development of more empathetic and intelligent human-computer interface.

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