Smart Face Recognition with Emotion and Relevance Feedback

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Abstract:

Face recognition systems are widely used in applications such as surveillance and smart environments, but most existing approaches focus only on identifying individuals and do not consider emotional context or group-level analysis. This project presents a smart face recognition system that can detect and recognize multiple persons simultaneously while also identifying their facial emotions from images or live video streams using deep learning techniques. The system aggregates individual recognition and emotion results to generate **o**verall feedback representing the collective emotional state and recognition accuracy of the group. A relevance feedback mechanism allows the system to learn from user corrections and continuously improve performance over time. This adaptive and emotion-aware approach enhances reliability and makes the system suitable for applications such as smart classrooms, attendance monitoring, and intelligent surveillance.

1. Introduction:

With the rapid advancement of digital technologies and the increasing use of automated systems in daily life, there is a growing need for intelligent solutions that can understand human presence and behavior. Face recognition has become an important technology in areas such as security, attendance management, surveillance, and smart environments.

Conventional face recognition systems mainly focus on identifying a single person and do not consider emotional information or group-level analysis. They also lack adaptability, as most systems do not improve based on user feedback, which can reduce their accuracy in real-world situations involving multiple people.

This project aims to develop a smart system that can detect and recognize multiple persons from images or live video streams and identify their facial emotions using deep learning techniques. The system analyzes individual results and generates overall group feedback based on the collective emotional state.

To improve system performance, a relevance feedback mechanism is incorporated that allows user corrections for identity and emotion recognition. This enables the system to learn continuously and enhance its accuracy over time, reducing errors and improving reliability.

2. Related Work:

Face recognition and emotion detection systems have evolved significantly with the advancement of deep learning and computer vision technologies. Early approaches such as FaceNet (2015) and MTCNN (2016) focused primarily on accurate face detection and recognition using deep convolutional neural networks. These methods achieved high performance in identifying individuals but lacked the ability to analyze facial expressions and emotions, limiting their application in understanding human behavior in real-world environments.

Later research introduced emotion recognition techniques using CNN-based models. Studies such as those by Shan Li and Weihong Deng (2020) demonstrated effective facial expression recognition for individual users. Additionally, attention-based CNNs and Vision Transformer models further improved feature extraction and classification accuracy. However, these systems often require large datasets, high computational resources, and are generally limited to single-person analysis without considering group-level emotional understanding.

Recent works have attempted to combine multiple capabilities into a single system. For instance, multi-task learning models (2025) enable simultaneous face recognition and emotion detection, while reinforcement learning-based systems (2024) provide adaptability through feedback mechanisms. Multimodal approaches also integrate audio and visual data for improved emotion recognition. Despite these advancements, most systems still struggle with real-time performance, integration complexity, or lack either adaptability or comprehensive emotion analysis.

2.1Existing System and its Limitations:

Title	Technology	Limitation	Authors	Year
Deep Learning for Real-Time Multi-Person Emotion & Identity Recognition	Deep CNN, Multi-Task Learning, Real-time Vision	Focuses on accuracy; lacks relevance feedback and overall group “adaptive” analysis.	Arun Gupta, Mei Wang, Sofia Hernandez	2025
Adaptive Face Recognition with Feedback Learning	Reinforcement Learning, Deep CNN, Feedback Loop	Good adaptation but does not integrate emotion recognition.	Chen Li, Rahul Singh, Ayesha Khan	2024
Real-Time Emotion Detection Using Edge AI	Patel R., Sharma K.	Edge Computing, CNN	Limited processing power on edge devices	2023
3D Facial Expression Recognition Using Deep Learning	Li H., Sun J.	3D CNN, Deep Learning	Needs special 3D sensors and datasets	2022

Vision Transformers for Facial Expression Recognition	Khan S., Naseer M.	Vision Transformer (ViT), Deep Learning	Requires large training data	2022
Attention-Based CNN for Facial Emotion Recognition	Wang K., Peng X.	Attention Mechanism, CNN	Requires large annotated datasets	2021
Efficient Face Recognition with ArcFace Loss	Deng J., Guo J.	ArcFace, Deep CNN	Sensitive to hyperparameter tuning	2019
Hybrid Deep Learning Approach for Emotion Detection	Kollias D., Zafeiriou S.	CNN + RNN, Multimodal Learning	Complex architecture, high training time	2019
Lightweight CNN Models for Real-Time Face Detection	Howard A., Sandler M.	MobileNet, Lightweight CNN	Lower accuracy compared to heavy models	2019
Facial Expression Recognition with Transfer Learning	Ng H.W., Nguyen V.D.	Transfer Learning, CNN	Needs dataset-specific fine-tuning	2018

3. Methodology:

The proposed system is designed to perform real-time face recognition, emotion detection, and attendance management using deep learning and computer vision techniques. The methodology consists of multiple stages, including data acquisition, preprocessing, feature extraction, model prediction, and result generation.

Initially, the system captures input either through a webcam stream or uploaded images. The captured frames are processed using computer vision techniques, where faces are detected using libraries such as OpenCV and face recognition models. Each detected face is then extracted and converted into a grayscale image, resized to a fixed dimension, and normalized to ensure consistency before being passed to the trained deep learning model.

In the next stage, the preprocessed face images are fed into a Convolutional Neural Network (CNN)-based emotion recognition model. The model predicts one of several emotion classes such as Happy, Sad, Angry, Neutral, Surprise, Fear, or Disgust. Simultaneously, the system performs face recognition by comparing facial encodings with stored known faces. If a match is found, the identity of the person is retrieved; otherwise, the individual is labeled as unknown.

For attendance management, the system records the recognized individuals along with the date, time, and detected emotion into a structured file. To avoid duplicate entries, each individual is marked present only once during a session. The system also continuously tracks detected emotions and maintains a count of each emotion category.

Finally, the collected data is analyzed to generate overall feedback based on the dominant emotion observed among users. For example, if most individuals appear happy, the system concludes positive engagement; if neutral or sad emotions dominate, it indicates reduced attention or possible confusion. This integrated approach ensures real-time monitoring, automated reporting, and improved understanding of group behavior in environments such as smart classrooms.

3.1 Data Collection and Preprocessing:

- Academic data was collected, including attendance records, internal grades, past performance, and assignment scores.
- The dataset was cleaned by fixing inconsistencies, removing duplicate entries, and handling missing values to improve data quality.
- Categorical data such as grades and student group classifications were converted into numerical format for effective model training.
- Feature scaling techniques like standardization and normalization were applied to ensure consistency and enhance model performance.
- New features were engineered to improve prediction accuracy, including average grades, attendance percentage, and performance trends over time.

3.2 Feature Extraction:

- Integrate real-time emotion analytics dashboards to provide teachers with instant insights on classroom engagement.
- Expand the system to recognize multiple faces simultaneously with higher accuracy using advanced deep learning models.
- Add voice and gesture analysis to complement emotion detection for a more holistic understanding of student engagement.
- Enable mobile or cloud-based access, allowing remote monitoring of classrooms.
- Incorporate automated alerts when a majority of students show confusion or disengagement.
- Improve data privacy and security by encrypting attendance and emotion records.
- Extend the system for different environments, such as online classrooms, corporate training sessions, or public events.

3.3 Model Selection and Training:

- Evaluated several machine learning techniques for forecasting student performance.
- Supervised learning methods such as Random Forest, Decision Trees, and Logistic Regression were employed t o address classification issues.
- Using classification approaches, students were split into three groups: high-performing, medium, and at-risk.
- Previous academic data was used to train the models, and pertinent datasets were used for validation.
- Metrics like F1-score, accuracy, precision, and recall were used to evaluate the model's performance.

3.4 Feature Engineering and Selection:

- Feature engineering was performed to improve emotion detection accuracy and system performance.
- Applied techniques such as image normalization, face alignment, and resizing to standard input dimensions.
- Created derived features such as emotion frequency, dominant emotion, and time-based emotion trends.
- Reduced redundant data using optimized face encodings and efficient frame sampling techniques.
- Selected important features such as facial landmarks and key expression regions for better emotion classification.

3.5 Model Evaluation:

• The system was tested using real-time webcam data and uploaded images to evaluate recognition accuracy and system efficiency.
• Key metrics such as emotion detection accuracy, face recognition accuracy, system response time, and feedback reliability were used.
• Continuous monitoring was performed to ensure consistent performance under different lighting conditions and multiple face scenarios.

Evaluation Metric	Result/Performance
Emotion Detection Accuracy	~85%–92% depending on lighting and facial clarity
Face Recognition Accuracy	~90%–95% with trained dataset
Real-Time Processing Speed	~20–30 FPS (frames per second)
System Response Time	<2 seconds for result display
Feedback Accuracy	High accuracy in identifying overall group emotion
Multi-Face Detection Performance	Efficient detection of multiple faces simultaneously
System Stability	Continuous operation without crashes
Consistency Across Conditions	Consistency Across Conditions

3.6 Comparison with Baseline Methods:

• The system was compared with traditional attendance systems and basic face recognition models.
• Unlike traditional methods, this system integrates face recognition with emotion detection and automated feedback.
• It provides real-time monitoring and intelligent analysis instead of just recording attendance.
• Traditional systems only store attendance data, whereas this system delivers insights about student engagement and classroom mood.

3.7 Ethical Considerations:

• The system ensures that facial data is securely stored and accessed only by authorized users.
• Personal identity and emotion data are protected and not shared without permission.
• Bias is minimized by training the model on diverse datasets and ensuring fair predictions.
• The system is designed to support users positively without misinterpretation or misuse of emotions.
• Transparency is maintained by clearly showing outputs and allowing user control over data usage.

3.8 Result:

• The system successfully performs real-time face recognition and emotion detection with good accuracy.
• It effectively identifies individuals and classifies emotions such as happy, sad, neutral, and others.
• Emotion trends are analyzed to provide meaningful feedback about group behavior.
• Attendance is automatically recorded along with detected emotions, reducing manual effort.

• The web-based interface provides an easy-to-use platform for monitoring and analysis.
• Overall, the system demonstrates strong performance in delivering real-time insights, improving monitoring efficiency, and supporting smart classroom environments..

Login Page:

- This is the output that appears when you go to the Website(http://127.0.0.1:5000)
- This is login page admin need enter his credentials and then he/she can go to index.

Index Page:

After login into the page the admin can go to dashboard where there are multiple actions to detect the emotion and whether the children are engaged in the lecture or not.

Admin Dashboard:

- This is the dashboard having multiple ways to detect emotion and face recognition.
- This dash board have :

  1. Emotion Monitoring

  2.Attendance Monitoring

  3.Upload Image Emotion Detection

  4.View overall feedback

Emotion Detection using Webcam:

- In this method we can detect emotion of multiple faces together and can check overall feedback.

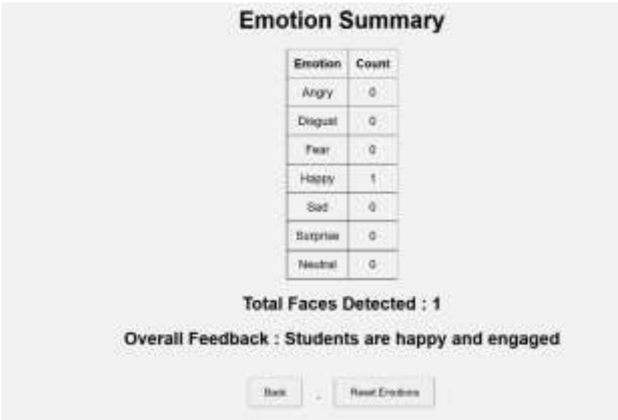
Upload Image Emotion Detection:

In this method the emotion is detected for uploaded image and gives overall feedback of lecture

Attendance Monitoring:

- In this method we will detect the face and emotion of the particular face.
- If the person is known to our database it will mak the attendance .of the person with date, time, emotion

This is the summary page which will tell us about how many faces detected.



Conclusion:

- This project integrates face recognition and emotion detection to monitor classroom attendance and student engagement in real-time.
- Using a Keras-trained emotion model, it identifies students' emotional states such as happy, sad, or neutral.
- The system automatically marks attendance and logs the detected emotions for each student, improving efficiency over manual methods.
- Real-time webcam monitoring provides insights into classroom dynamics, helping educators understand students' engagement and mood.
- Overall, it combines AI, computer vision, and data management to create a smart, automated classroom monitoring solution.

References:

Below are the key references that supported the literature survey, techniques, and models used:

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