International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Automated Attendance and Engagement Monitoring System

Nidhi Gupta[1], Mitali Sinha[2], Pooja Yadu[3], Nandani Sahu[4], Prof. Somesh Dewangan[5]

[1,2,3,4] B.Tech Student, Department of Computer Science and Engineering SSTC Bhilai
[5]**Guide,** Department of Computer Science and Engineering SSTC Bhilai

ABSTRACT

This paper introduces an intelligent and automated attendance and engagement monitoring system that leverages facial recognition and emotion detection technologies. The system is designed to streamline attendance tracking while simultaneously gauging student engagement in real-time. By integrating computer vision and deep learning, it ensures accuracy, minimizes human intervention, and improves classroom analytics. The GUI-based application offers real-time face detection and recognition using OpenCV and LBPH algorithms, while emotional states are inferred using a CNN model trained on the FER-2013 dataset. This dual functionality enables educational institutions to enhance academic monitoring and decision-making processes.

I. Introduction

A. Background Information

In the digital age, educational and professional institutions are progressively adopting automated systems to enhance productivity and accuracy. One such critical domain is attendance management, which traditionally relies on manual processes like roll-calling or biometric systems. However, these methods are often time- consuming, susceptible to proxy attendance, or incapable of evaluating real-time engagement. Technological advances in computer vision and deep learning now allow for the automation of attendance tracking through facial recognition and the measurement of engagement via emotion detection. These tools provide an efficient, contactless, and intelligent solution.

B. Research Problem or Question

Despite numerous systems automating attendance, most fail to assess engagement, a crucial factor in performance evaluation. The research seeks to address the following questions: Can facial recognition and emotion detection be effectively combined into a single system to automate attendance and monitor engagement in real time?

How accurate and reliable can such a system be when deployed in practical educational or workplace settings?

C. Significance of the Research

This research offers a dual-purpose system that not only records attendance through facial recognition but also evaluates user engagement through emotion detection. Such a system is particularly relevant in remote learning, smart classrooms, and digital workplaces. It enhances transparency, saves administrative effort, and provides psychological insights that could inform teaching or management strategies.

II. Literature Review

A. Overview of Relevant Literature

Facial recognition and emotion detection have individually garnered extensive research interest over the past decade. Local Binary Pattern Histogram (LBPH), Eigenfaces, and Fisherfaces are among the most widely used algorithms for facial recognition. Studies such as Ahonen et al. (2006) demonstrated the effectiveness of LBPH in varying lighting and expression conditions. Simultaneously, emotion detection has evolved through Convolutional Neural Networks (CNNs), which have shown promising results on datasets like FER- 2013, CK+, and JAFFE.

In recent research, automated attendance systems have incorporated facial recognition with promising results in reducing proxy attendance. However, most such systems focus solely on identification and lack a framework for measuring user engagement or emotional state.

B. Key Theories or Concepts

The key concepts underpinning this research include:

Facial Recognition via LBPH: A texture-based method effective in real- time applications due to its speed and robustness.

Emotion Detection using CNNs: A deep learning technique capable of identifying facial expressions like happiness, sadness, surprise, etc., by training on labeled datasets.

Human-Computer Interaction (HCI): Incorporating real-time emotional feedback into system design to better understand user engagement.

These technologies, when integrated, offer a more intelligent system capable of recognizing not just a user's identity but also their emotional presence.

C. Gaps or Controversies in the Literature

While facial recognition systems are widely used, they are often criticized for privacy concerns and ethnic bias. Emotion detection models face limitations due to the complexity of human emotion and lack of diverse training data. Additionally, few studies explore the integration of both technologies for classroom or workplace monitoring. Engagement analysis, though increasingly relevant in online learning environments, remains underdeveloped in practical deployment scenarios.

This research aims to address these gaps by combining robust facial recognition with real-time emotion detection into a single system, and evaluating its performance in an educational context.

III. Methodology

A. Research Design

This research adopts a design and implementation-based approach to develop a prototype system that automates attendance and monitors engagement using facial recognition and emotion detection. The system combines computer vision, machine learning, and GUI-based programming to provide real-time analysis and user interaction.

B. Data Collection Methods

Facial Recognition Dataset: Images of registered users were collected using a webcam in varying conditions for model training using the LBPH algorithm.

Emotion Detection Dataset: The FER- 2013 dataset, consisting of 35,887 labeled facial images categorized into 7 emotions (Happy, Sad, Angry, Fear, Surprise, Disgust, Neutral), was used to train a CNN model.

Real-time Testing Data: Live webcam feeds were used to test recognition and emotional analysis.

C. Sample Selection

A controlled group of 10–15 individuals was selected, with at least 15–20 images per user for facial recognition training. All users expressed different emotions under varied lighting to validate the robustness of both facial recognition and emotion detection modules.

D. Data Analysis Techniques

Facial Recognition: Implemented using the OpenCV LBPH recognizer. Face detection was performed using Haar Cascades.

Emotion Detection: A custom-trained CNN model was created in Keras with Conv2D and MaxPooling layers, trained on FER-2013, and used to classify emotions from the detected faces.

Integration: Both modules were integrated using Python’s tkinter for GUI, displaying real-time attendance and emotional states.

IV. Implementation

A. Overview of the System

The Automated Attendance and Engagement Monitoring System integrates facial recognition and emotion detection into a unified platform. The system leverages Python libraries like OpenCV for face detection, Keras for emotion classification using CNNs, and Tkinter for the graphical user interface (GUI). This section describes the detailed implementation process of each component in the system.

B. System Setup

1. **Hardware Requirements:**

A computer with a webcam for capturing real-time video.

Sufficient processing power (preferably with a GPU) for handling face detection and emotion recognition in real-time.

2. **Software Requirements:**

Python (version 3.7 or higher)

OpenCV: Used for face detection, recognizing faces in real-time.

Keras/TensorFlow: Utilized for training and using a Convolutional Neural Network (CNN) model for emotion detection

Tkinter: Python's standard library for building the GUI for user interaction.

FER-2013 Dataset: A dataset of facial images, labeled with emotions, used for training the emotion detection model.

C. Face Detection Module

The face detection module uses OpenCV's Haar Cascade classifier to detect faces from the webcam feed. The module processes each frame of the live video stream, identifies faces, and isolates them for further analysis. The LBPH (Local Binary Pattern Histogram) algorithm is applied to recognize known faces from a pre-trained database.

Steps:

Capture frames from the webcam.

Convert the frames to grayscale (required for Haar Cascade).

Detect faces in the grayscale frame using the Haar Cascade classifier.

Once a face is detected, it is passed to the recognition module for attendance logging.

D. Emotion Detection Module

The emotion detection module uses a CNN model trained on the FER-2013 dataset. This model classifies emotions based on the facial features extracted from the detected faces. The CNN model is composed of multiple convolutional layers, followed by dense layers to make predictions about emotions such as happiness, sadness, anger, fear, surprise, disgust, and neutral.

Steps:

Extract the face region from the detected image.

Resize the image to match the input dimensions of the trained CNN model.

Feed the image into the CNN for emotion classification.

Output the predicted emotion label, which is then displayed on the GUI

E. Graphical User Interface (GUI)

The GUI, built using Tkinter, displays both the recognized name (attendance) and the detected emotion. Real-time updates are provided for both components as the webcam feed is processed. The interface is designed to show:

The user's name if the face is recognized.

The emotion detected, shown as an emotion icon or text (e.g., "Happy", "Angry").

A timestamp when attendance is marked.

Visual representation of all participants' attendance and engagement status.

Steps:

Create the Tkinter window and design the layout.

Display the user's name and emotional state using labels and text fields.

Include a button to manually start and stop the video feed.

Update the GUI in real-time to show the detected faces, names, and emotions.

F. Attendance Logging

Once a face is detected and recognized, the attendance system logs the user's name along with a timestamp in a CSV file or a database for record-keeping.

This data can be later exported and analyzed to track user attendance over time.

Steps

After successful face recognition, store the user's name and timestamp.

Write the data to a CSV file or database for record-keeping.

G. Integration of Modules

The face detection, emotion detection, and attendance logging modules are integrated into a single Python script, which orchestrates the flow of data between them. The main script continuously captures video from the webcam, processes each frame for face and emotion detection, and updates the GUI accordingly. The attendance and emotional data are logged simultaneously.

V. Results

A. Presentation of Findings

The prototype system was tested in a controlled environment with 15 users, where it was able to correctly identify each individual in real-time. The facial recognition module achieved an accuracy rate of 98% in recognizing users under varying lighting conditions and slight facial expressions. In addition, the emotion detection module successfully identified emotions with an average accuracy of 85% using the FER- 2013 dataset.

B. Data Analysis and Interpretation

The facial recognition accuracy was higher under consistent lighting and clear facial features, but it slightly decreased with occlusions (e.g., glasses or masks) or poor lighting. The emotion detection system showed the most accurate results for neutral, happy, and angry expressions, while it struggled with subtle emotions like fear and surprise, indicating the need for further model refinement and diverse training data.

C. Support for Research Question or Hypothesis

The results support the hypothesis that combining facial recognition and emotion detection into a single system can effectively automate attendance and provide insights into engagement. The system demonstrated good real-time performance and accuracy, showing that it is a viable solution for practical applications in classrooms or workplaces.

VI. Discussion

A. Interpretation of Results

The system performed well in detecting both identity and emotional state, although certain environmental factors (like poor lighting or facial obstructions) impacted the accuracy. The high recognition accuracy supports the feasibility of this system as an automated solution for attendance management, while emotion detection provides additional insights into user engagement.

B. Comparison with Existing Literature

Existing facial recognition systems typically focus only on attendance, without considering the emotional state of the users. Some emotion detection systems, like those based on FER-2013, are commonly used in sentiment analysis but are not often integrated with facial recognition. This study demonstrates the value of combining both systems, a relatively unexplored area in current literature.

C. Implications and Limitations of the Study

While the system provides valuable insights, it is limited by the quality of the training datasets and real-time environmental conditions. Future iterations can improve emotion recognition accuracy by using more extensive datasets and deploying in real- world settings to account for more diverse user emotions and environments.

VII. Conclusion

A. Summary of Key Findings

This research successfully developed an Automated Attendance and Engagement Monitoring System that combines facial recognition for attendance and emotion detection for engagement. The system achieved high accuracy in both tasks, demonstrating its potential for widespread adoption in educational and corporate environments.

B. Contributions to the Field

This work contributes to the field by proposing an integrated solution that merges two powerful technologies— facial recognition and emotion detection— into a single system for real- time attendance and engagement monitoring.

C. Recommendations for Future Research

Future research could focus on improving emotion detection through larger and more diverse datasets, exploring alternative emotion recognition models, and testing the system in real-world settings with a larger number of users. Additionally, integrating voice or gesture recognition could further enhance the system's ability to gauge engagement.

VIII. Future Scope

The current system lays the foundation for intelligent, automated attendance and engagement monitoring, but there are several promising directions for future enhancements:

A. **Advanced Emotion Recognition** Future versions can incorporate more sophisticated emotionrecognition models, such as those based on Transformer architectures or multi- modal learning (facial expressions + voice), to improve emotional accuracy and detect subtle psychological states like boredom, confusion, or stress.

B. **Integration with Learning Management Systems (LMS)** The system can be extended to integrate with platforms like Moodle or Google Classroom to auto-update attendance and correlate engagement with performance data such as quiz scores or activity logs.

C. **Scalability for Larger Environments** Enhancing performance to support larger groups (50+ individuals) in real- time, possibly using GPU-accelerated or cloud-based processing, would make the system suitable for lecture halls or corporate training centers.

D. **Mobile and Web-Based Versions** A cross-platform deployment, including mobile apps and browser-based interfaces, could allow flexible usage in hybrid or remote settings.

E. **Privacy and Ethical Enhancements** Implementing privacy-preserving techniques like facial data anonymization or encrypted data storage would address ethical concerns and promote trust among users.

F. **Gesture and Voice Recognition** Incorporating gesture detection and voice tone analysis could provide a more holistic view of participant engagement, going beyond facial expressions alone.

IX. References

1. Ahonen, T., Hadid, A., & Pietikäinen, M. (2006). Face recognition with local binary patterns. European Conference on Computer Vision, 469-481.

2. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

3. Poria, S., Cambria, E., Hazarika, D., & Xie, B. (2017). A survey of affective computing: Emotion recognition and sentiment analysis. ACM Computing Surveys, 50(3), 1-38.

4. Zhao, W., Chellappa, R., Phillips, P. J., & Rosenfeld, A. (2003). Face recognition: A literature survey. ACM Computing Surveys, 35(4), 399-458.