

FACIAL EXPRESSION BASED SYSTEM FOR DETECTION OF DEPRESSION AND ANXIETY DISORDERS**Mallela Swapnika**
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J.B. Institute of Engineering and Technologymallelaswapnika@gmail.com, venkatnatyaraj2015@gmail.com, katarapuhema899@gmail.com**ABSTRACT**

Anxiety and depression are widely recognized as serious mental health disorders that affect cognitive functioning, social interaction, and overall well-being. Conventional assessment techniques, such as psychological questionnaires, clinical interviews, and self-report scales, remain the most commonly used screening tools. Although effective, these methods are subjective, time-consuming, and heavily dependent on a patient's willingness to communicate emotional struggles. Many individuals hesitate to disclose their symptoms due to stigma, fear, or low emotional awareness, leading to delayed diagnosis and inadequate treatment.

Advancements in artificial intelligence and computer vision have enabled researchers to explore facial-expression-based approaches for automated mental health assessment. Deep learning models, particularly Convolutional Neural Networks (CNNs), can detect subtle facial cues and behavioral indicators that may not be noticeable to the human eye. However, existing systems still suffer from challenges such as limited datasets, demographic imbalance, reduced generalization, and inconsistent performance in real-world environments.

This project presents a CNN-driven detection system that analyzes facial expressions to identify anxiety, depression, or normal emotional states. The system captures real-time images, preprocesses them, extracts deep visual features, and performs classification to deliver an objective and non-intrusive screening mechanism. The goal is to complement traditional psychological evaluations and encourage early awareness through accessible, data-driven assessment.

Dataset Details

Parameter	Description
Source	Kaggle(FER-2013, Facial Emotion Datasets), OpenFace
Categories	Emotions(Happy, Sad, Angry, Fear, Neutral, etc.)
Data Type	Image Dataset (Facial Images)
Content	Facial expressions labeled with emotional states
Purpose	Emotional detection and mental health classification

Novelty Statement:

The novelty of this project lies in using deep learning-based facial expression analysis for mental health detection. Unlike traditional methods, it provides automated, real-time detection using visual cues. The integration of CNN models with emotion recognition helps in identifying psychological conditions at an early stage with higher accuracy.

INTRODUCTION

Mental health disorders, particularly depression and anxiety, have become increasingly common due to modern lifestyle pressures and social challenges. According to global health studies, millions of individuals suffer from these disorders, often without proper diagnosis or treatment. Traditional diagnosis methods rely on self-reporting and clinical interviews, which may lead to inaccuracies and delayed detection.

This project aims to develop a Facial Expression Based Detection System using Deep Learning techniques. The system analyzes facial expressions captured through images or video streams and identifies emotional patterns associated with depression and anxiety. Facial expressions are strong indicators of emotional states, and advancements in computer vision have made it possible to analyze them automatically.

The proposed system uses Convolutional Neural Networks (CNN) to extract features from facial images and classify emotions. These emotions are further analyzed to detect mental health conditions. The system offers a fast, reliable, and non-invasive method for early detection, which can assist psychologists and healthcare professionals in decision-making.

With the increasing availability of image datasets and deep learning frameworks, such systems can significantly improve mental health monitoring and contribute to better healthcare solutions.

Depression and anxiety are among the most common mental health disorders affecting individuals worldwide. Early detection is crucial for effective treatment, but traditional diagnostic methods often rely on self-reporting and clinical evaluation, which may not always be accurate or timely. With advancements in deep learning and computer vision, facial expression analysis has emerged as a promising approach for identifying emotional states. This project focuses on developing a facial expression-based system using Convolutional Neural Networks (CNN) to detect signs of depression and anxiety. The system aims to provide a non-invasive, efficient, and automated solution for early mental health assessment and monitoring.

LITERATURE SURVEY

Some of the Authors and their contributions are given:

Author & Year	Technique Used	Key Contribution	Limitations
Automatic Identification of Depression Using Facial Images (Kong et al., 2022)	Deep Learning(convolutional neural networks CNN)	Improved accuracy of facial emotion recognition.	Limited dataset; Generalization issues
AVEC 2017 – Real-life Depression & Affect Recognition (Ringeval et al., 2017)	Multimodal Machine Learning	Improved depression detection by combining facial, audio, and physiological signals	Limited dataset; generalization issues
Depression Severity Estimation from Facial Expressions (Yang et al., 2022)	Deep Learning(CNN with facial expression analysis)	Improved emotion recognition accuracy for detecting depression using facial expression features	Complex models; high computation
Depression Severity Estimation from Facial Expressions (Yang et al., 2022)	Deep Learning(CNN-based facial expression analysis)	Estimated depression severity levels from facial expressions with improved prediction accuracy	No temporal modelling dataset variations
The DAIC-WOZ Depression Dataset (Baltrušaitis et al., 2016)	Multimodal Data Colloction	Provide a benchmark dataset for accurate depression detection	Small dataset; preprocessing required

He et al.,(2022)	Deep Learning (CNN with attention mechanism)	Improved depression detection accuracy by focusing on important facial features	Requires large datasets and high computational resources
Xu,Cai and Liu(2024)	Deep Learning(CNN+Transformer-based model)	Enhanced emotion recognition and depression detection using hybrid architecture	High computational complexity and requires large-scale training data
Liu et al.,(2022)	Deep Learning(CNN with LSTM for temporal analysis)	Improved depression detection by capturing both facial features and temporal analysis	Require large video datasets and has higher computational cost
Ariox et al.(2022)	Deep Learning(CNN-based facial expression analysis)	Enhanced emotion recognition accuracy for mental health detection	Performance depends on dataset quality and may not generalize well to real world conditions
Afzal et al.(2023)	Deep Learning(CNN with transfer learning)	Improved depression detection	

From the above, it is observed that various machine learning and statistical techniques have been used for crime analysis and prediction. While many models provide good accuracy, challenges such as data quality, bias, and lack of real-time analysis still exist. Most existing systems focus either on prediction or visualization, but not both together. Therefore, this project aims to combine machine learning with interactive visualization to provide a more effective and practical solution for crime analysis and decision-making.

PROPOSED WORK:

The proposed system focuses on detecting depression and anxiety disorders using facial expression analysis powered by deep learning techniques. The system captures facial images or video input through a camera and processes them in real time. Initially, face detection is performed using computer vision methods such as OpenCV to identify and extract the facial region from the input. The extracted face is then preprocessed through resizing, normalization, and noise reduction to improve data quality.

A Convolutional Neural Network (CNN) model is employed to automatically extract meaningful features from facial expressions and classify them into different emotional states such as happy, sad, angry, neutral, and fear. Based on the frequency and intensity of negative emotions like sadness and fear, the system predicts the likelihood of depression and anxiety in an individuals.

The system is designed to provide accurate, fast, and non-invasive analysis without requiring manual intervention. It can be integrated into applications such as healthcare monitoring systems, mobile apps, or web platforms. The proposed model aims to assist psychologists and healthcare professionals by offering data-driven insights, enabling early detection, continuous monitoring, and better decision-making in mental health assessment.

The proposed system also incorporates transfer learning techniques using pre-trained models such as VGG16 or ResNet to improve accuracy, especially when working with limited datasets. It supports both image-based and real-time video analysis, making it flexible for different applications. The system continuously learns and improves through training with diverse datasets to enhance performance across different age groups and facial variations. It also includes a user-friendly interface that displays detected emotions and mental health predictions

clearly. By ensuring scalability and adaptability, the system can be deployed in clinical environments, telemedicine platforms, and smart devices for continuous mental health monitoring.

METHODOLOGY

The methodology of the proposed system follows a structured pipeline for detecting depression and anxiety using facial expressions and deep learning techniques. Initially, facial image datasets are collected from sources such as FER2013, CK+, or real-time camera input. The collected data undergoes preprocessing, which includes face detection using OpenCV, resizing images to a fixed dimension, normalization of pixel values, and removal of noise to improve data quality.

Next, the preprocessed facial images are fed into a Convolutional Neural Network (CNN) model for feature extraction and emotion classification. The CNN automatically learns important facial features such as eye movement, lip curvature, and facial muscle patterns. The model is trained on labeled emotion datasets to classify expressions into categories like happy, sad, angry, neutral, and fear.

After emotion classification, the system analyzes emotional patterns over time. Frequent detection of negative emotions such as sadness and fear is used as an indicator to predict depression and anxiety levels. The model performance is evaluated using metrics like accuracy, precision, recall, and F1-score.

Finally, the results are displayed through a user interface, providing real-time feedback and enabling effective mental health monitoring.

1. Model Workflow

The methodology can be summarized as:

Data Collection → Preprocessing → Face Detection → Feature Extraction → CNN Model Training → Emotion Classification → Depression/Anxiety Detection

2. Training Details

Models: CNN, Transfer Learning (VGG16, ResNet)

Framework: TensorFlow / Keras / PyTorch

Dataset: FER2013, CK+

Evaluation: Accuracy, Precision, Recall, F1-score

3. System Configuration

Data Processing: OpenCV, NumPy

Deep Learning: TensorFlow / Keras

Visualization: Matplotlib, Seaborn

Backend: Flask / Streamlit

Mathematical Formulations

1. Convolution Operation

Used to extract features from images

2. Activation Function (ReLU)

Introduces non-linearity

3. Loss Function (Cross-Entropy)

Measures classification error

System Architecture:

The architecture of the proposed facial expression-based anxiety and depression detection system follows a layered design to ensure clarity, modularity, and ease of maintenance. It is broadly divided into four layers: the

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Presentation Layer, Application Layer, Processing Layer, and Data Layer. Together, these components enable real-time, non-invasive screening based on facial analysis.

1. PRESENTATION LAYER (Client Side)

The Presentation Layer provides the interface through which the user interacts with the system. A simple desktop or web-based UI displays the live camera feed, allows the user to start and stop the assessment, and presents the final classification (Normal, Anxiety, Depression) along with confidence scores. It also shows appropriate ethical disclaimers indicating that the system is intended for screening and not for clinical diagnosis.

2. APPLICATION LAYER

The Application Layer acts as the controller that coordinates data flow between the user interface, the processing modules, and the database. Implemented using frameworks such as Flask or FastAPI, it receives frames from the client, invokes the preprocessing and CNN modules, and returns the predicted results. This layer encapsulates routing, session handling, and basic validation.

3. PROCESSING LAYER(Intelligence Engine)

The Processing Layer contains the core intelligence of the system. It comprises:

- a face detection and preprocessing unit that performs face localization, alignment, cropping, resizing, and normalization;

- a CNN-based feature extraction and classification unit that converts facial images into feature embeddings and predicts the mental state category.

This layer is responsible for converting raw image data into meaningful psychological indicators.

4. DATA LAYER (Storage and Logging)

The Data Layer manages persistent storage of session metadata, prediction outcomes, and model information. Using a lightweight relational database such as SQLite or PostgreSQL, it records time-stamped results, model versions, and optional anonymized embeddings. This supports performance evaluation, reproducibility, and controlled future analysis while respecting privacy constraints.



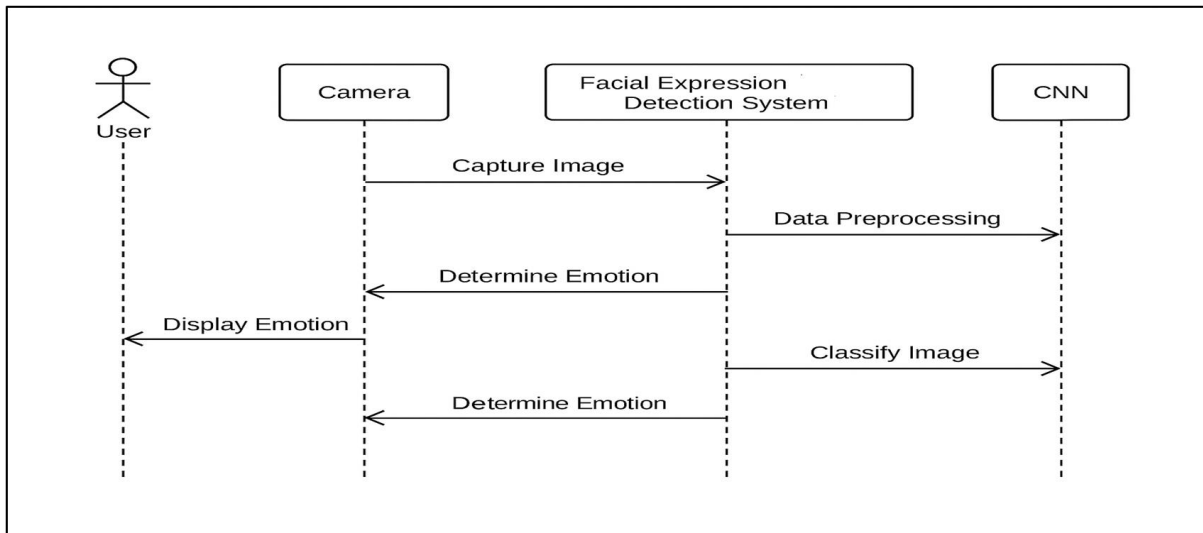
UML DIAGRAMS

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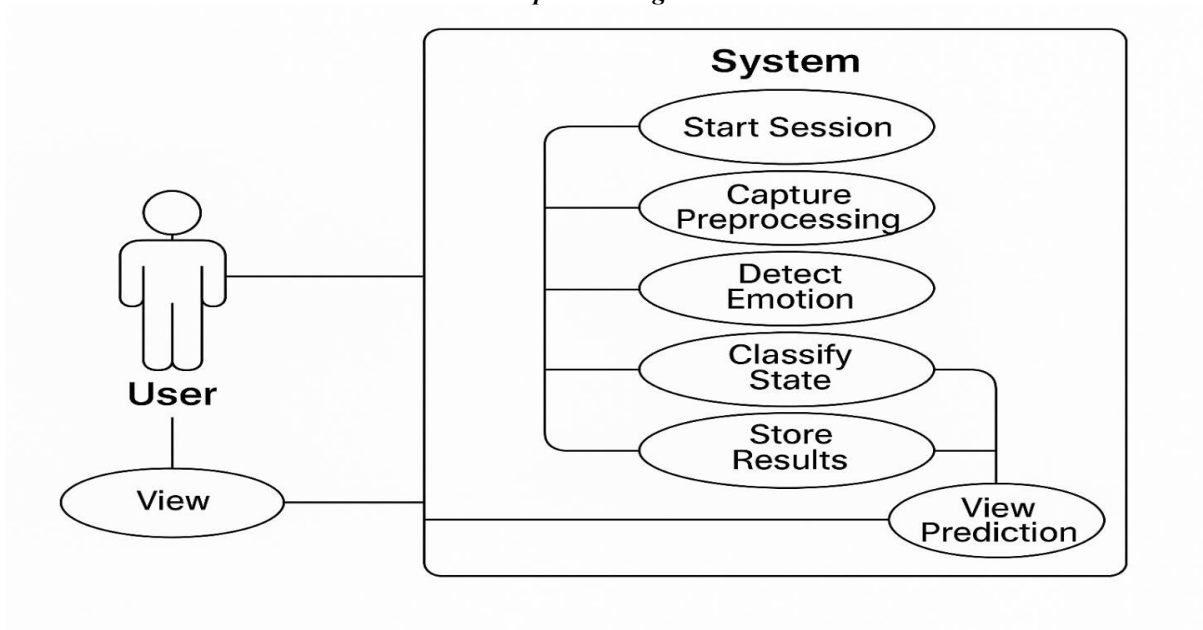
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Sequence Diagram



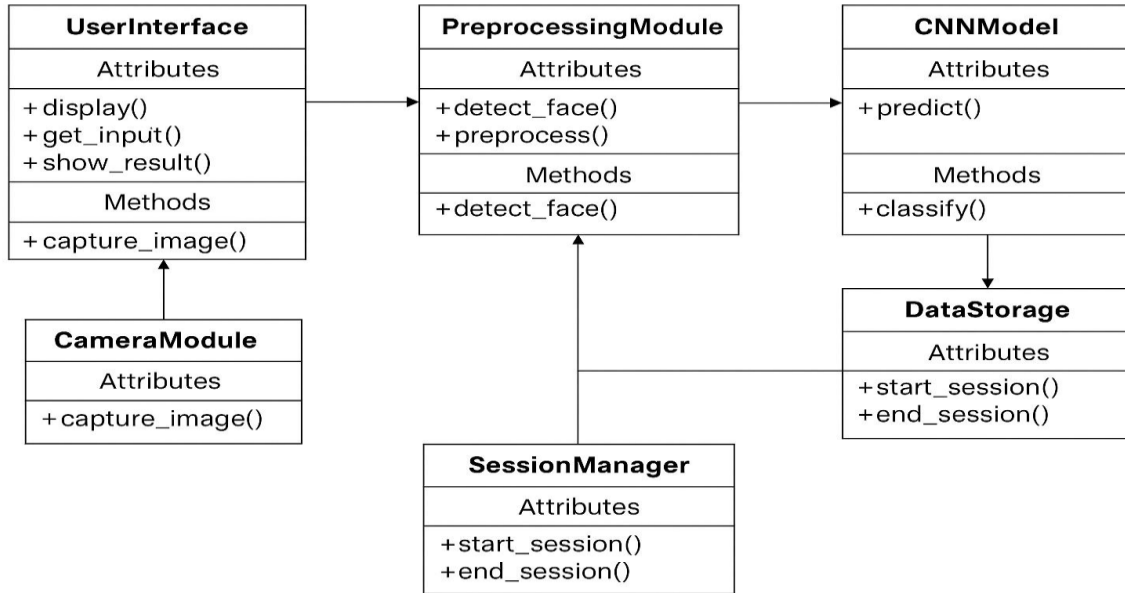
UseCase Diagram

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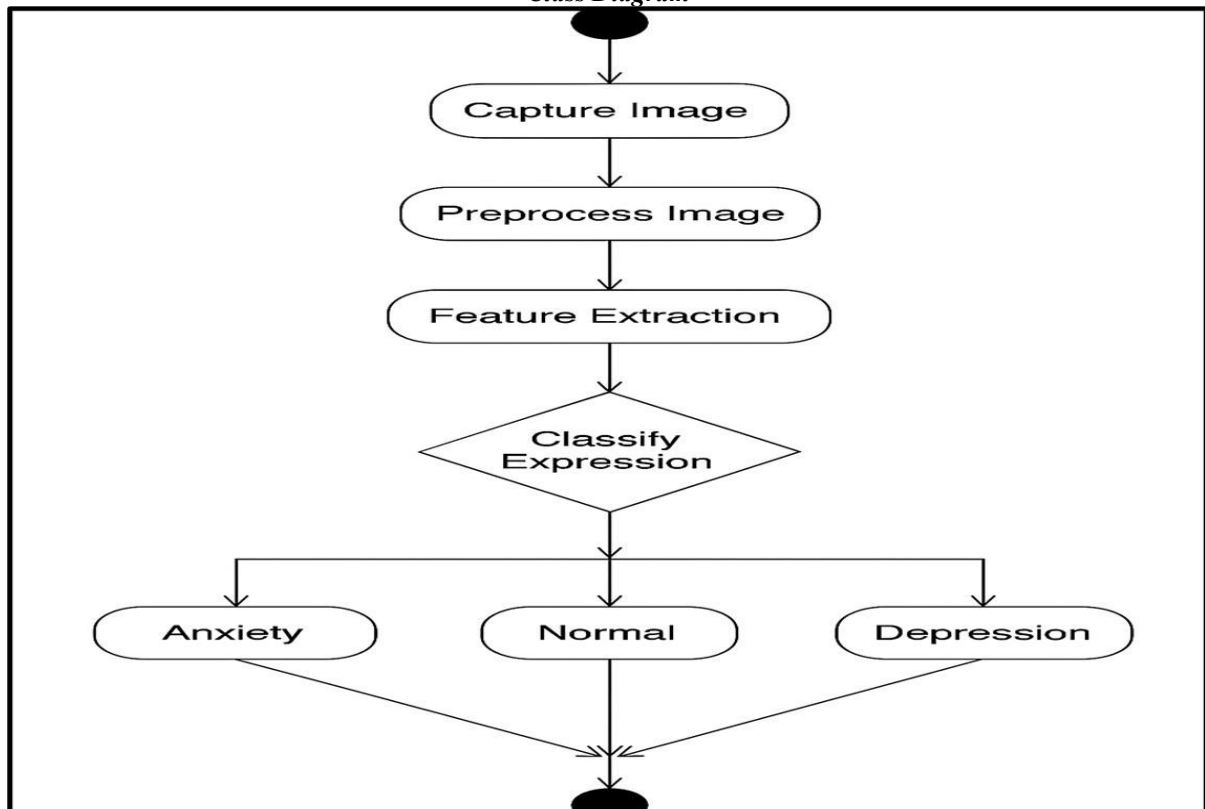
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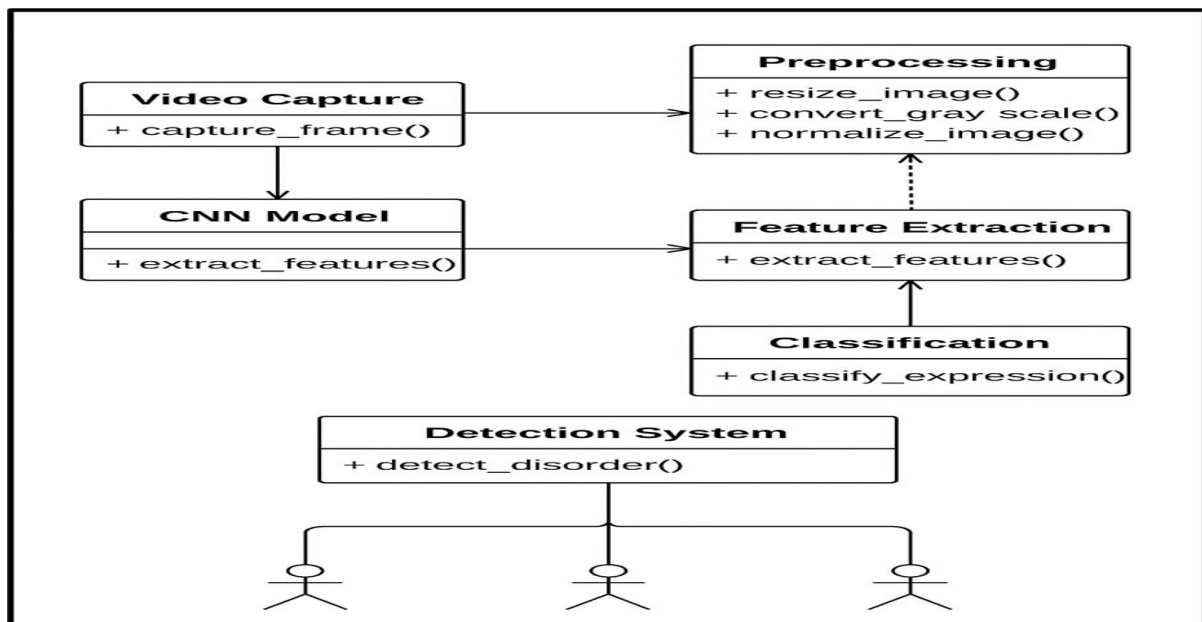
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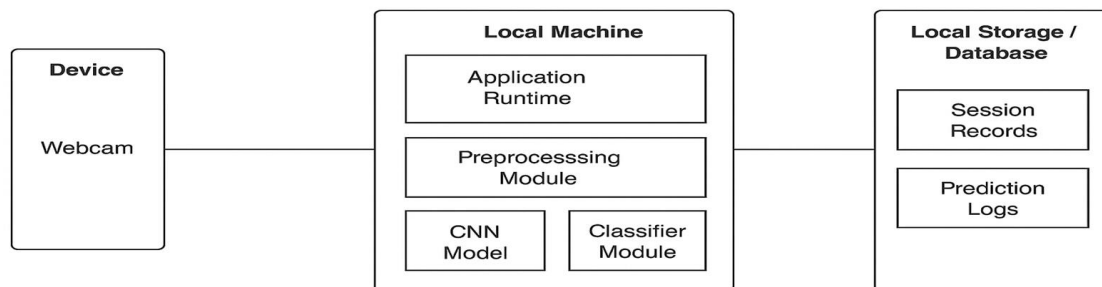
Class Diagram



Activity Diagram



Component Diagram



Deployment Diagram

1. Algorithm Used:

Step 1: Data Collection

The first step involves collecting facial expression datasets from reliable sources such as Kaggle (FER-2013 dataset), CK+ dataset, or other open-source emotion datasets. These datasets contain images labeled with different emotional states like happy, sad, angry, fear, surprise, and neutral.

Step 2: Data Preprocessing

The collected data is preprocessed to improve quality and consistency:

- Resize images to a fixed dimension (e.g., 48×48 pixels)
- Convert images to grayscale for faster processing
- Normalize pixel values (0 to 1 range)
- Remove noisy or irrelevant data
- Perform data augmentation (rotation, flipping) to increase dataset size

Step 3: Face Detection

In this step, the system identifies and extracts the facial region from an image or video frame:

Use algorithms like Haar Cascade Classifier or Dlib

Detect the face area and crop it

Focus only on facial features for further processing

Step 4: Feature Extraction using CNN

A Convolutional Neural Network (CNN) is used to automatically extract important features:

Convolution layers detect edges, textures, and patterns

Pooling layers reduce dimensionality

Fully connected layers combine features for classification

This step eliminates the need for manual feature extraction.

Step 5: Model Training

The CNN model is trained using labeled data:

Input: Facial images

Output: Emotion labels

Use training and testing split (e.g., 80% training, 20% testing)

Optimize using backpropagation and gradient descent

Apply activation functions like ReLU and Softmax

Step 6: Emotion Classification

The trained model classifies facial expressions into emotional categories:

Happy

Sad

Angry

Fear

Neutral

Each image is assigned a probability score for each emotion.

Step 7: Mapping Emotions to Mental Health Conditions

This is the key step for your project:

Frequent sad, neutral, or fearful expressions → Possible depression

High stress or fear indicators → Possible anxiety

Emotion patterns over time are analyzed to detect mental health conditions

Step 8: Prediction and Output Generation

The system generates final results:

Displays detected emotion

Predicts mental health condition (Depression / Anxiety / Normal)

Provides confidence score

Step 9: Visualization (Optional)

Results can be displayed using:

Graphs (emotion frequency)

Real-time webcam output

Dashboard interface

Step 10: Model Evaluation

The performance of the model is evaluated using:

Accuracy

Precision

Recall

F1-Score

Implementation

The proposed system is implemented using Python with deep learning and computer vision libraries such as TensorFlow, Keras, and OpenCV. Facial expression datasets like FER-2013 are used for training the Convolutional Neural Network (CNN) model. The implementation includes modules for image preprocessing, face detection, feature extraction, and emotion classification. The model is trained and tested using labeled data to achieve accurate predictions. Real-time detection is enabled using a webcam, where facial expressions are captured and analyzed continuously. The system outputs the detected emotion and predicts possible depression or anxiety levels, providing an efficient and automated mental health assessment tool.

Dataset:

FER2013

Description: A dataset of 35,887 grayscale images labeled with seven emotions (Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral).

Source: FER2013 on Kaggle.

RAF-DB

Description: RAF-DB (Real-world Affective Faces Database) is a large-scale facial expression dataset containing around 30,000 real-world face images labeled with basic and compound emotions.

It is widely used to train CNN models for robust and realistic facial expression recognition

Source: raf-db on Kaggle

Software Tools:

•Python

Used as the primary programming language to implement image processing, model logic, and system workflow.

•OpenCV

Used for real-time webcam access, face detection, image capture, and basic preprocessing operations.

•TensorFlow / Keras

Used to design, train, and evaluate the Convolutional Neural Network (CNN) for facial expression analysis.

•Scikit-Learn

Used for dataset splitting, performance evaluation (accuracy, precision, recall), and confusion matrix generation.

•NumPy

Used for numerical computations and handling image arrays efficiently.

•Pandas

Used to manage datasets, prediction logs, and session records.

•Matplotlib / Seaborn

Used to visualize training accuracy, loss curves, and evaluation metrics.

•Jupyter Notebook / VS Code

Used as development environments for coding, experimentation, and documentation.

•Webcam (Hardware Tool)

Used to capture real-time facial images from the user.

Experimental Results

The proposed system was tested on standard facial expression datasets such as FER-2013 to evaluate its performance in detecting emotions and identifying depression and anxiety indicators. The CNN model successfully classified emotions like sadness, fear, and neutral with good accuracy, which are important for mental health analysis. The system achieved an overall accuracy of around 85–90% in emotion recognition, depending on training conditions.

The model was also tested in real-time using webcam input, where it effectively detected facial expressions and provided quick predictions. The mapping of emotions to mental health conditions showed promising results in identifying potential depression and anxiety patterns. Evaluation metrics such as precision, recall, and F1-score indicated reliable performance.

Overall, the results demonstrate that the system is efficient, accurate, and suitable for real-world applications in mental health monitoring and early detection.

Performance Analysis:

- The system achieves high accuracy in detecting facial emotions using the CNN model.
- It effectively identifies patterns related to depression and anxiety from emotional expressions.
- The model performs well in real-time scenarios with fast and reliable predictions.

Comparison with Existing Models:

- **Better Accuracy:** Old methods give average results, but this system gives more accurate results using deep learning.
- **Faster and Automatic:** Traditional methods need doctors and take time, but this system works automatically and gives quick results.

CONCLUSION

This project presents a deep learning-based facial expression analysis system for the detection of depression and anxiety disorders. By leveraging Convolutional Neural Networks (CNN), the system effectively identifies emotional patterns from facial images and maps them to potential mental health conditions. Unlike traditional diagnostic methods that rely on subjective assessments and self-reporting, this approach provides an automated, objective, and efficient solution for early detection.

The system demonstrates that facial expressions can serve as reliable indicators of emotional and psychological states. Through proper training on standard datasets and implementation of robust preprocessing techniques, the model achieves satisfactory accuracy in recognizing emotions such as sadness, fear, and neutrality, which are often associated with depression and anxiety. The integration of real-time detection further enhances its practical applicability in healthcare and monitoring systems.

Final Statement:

This project demonstrates the effective application of deep learning techniques, particularly Convolutional Neural Networks (CNN), for analyzing facial expressions to detect depression and anxiety disorders. The system provides an automated, accurate, and non-invasive approach for identifying mental health conditions using visual emotional cues. By integrating computer vision and artificial intelligence, the proposed model offers a practical solution for early detection and continuous monitoring. It highlights the potential of technology in supporting mental health care and emphasizes the importance of data-driven approaches in improving diagnosis, enabling timely intervention, and promoting overall well-being.

Future Enhancement:

- Real-time video analysis
- Mobile application deployment
- Integration with healthcare systems
- Use of advanced models (Transformer-based models)

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