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Emotion Recognition System For Mental Health Monitoring

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Abstract: Recognizing and identifying emotions is a key element of understanding mental health that can ideally lead to better emotional well-being. The project combines facial recognition of emotions with data analysis to assess for conditions such as anxiety and depression. This detects and provides real-time emotion profiles with individual perspectives for healthcare workers via deep learning. To detect facial expression, Convolutional Neural Networks (CNNs) are utilized along a series of facial characteristics to extract essential details. Artificial Neural Networks can be made to classify emotions and, thus, play a role in understanding patterns related to mental health conditions; e.g., feeling drowsy, anxious. This system essentially links technology and health care, effectively equipping mental health professionals with modern, data-driven tools for on-time and personalized interventions.

Keywords: Artificial Neural Network, Convolutional Neural Network.

I. INTRODUCTION

Mental health issues have taken centre stage in public health affairs in recent years. Depression and anxiety alone could rock the lives of millions of people globally. Early detection and intervention are imperative for improving mental health outcomes, yet traditional methods for mental health assessment typically rely on subjective self- reporting or rare clinical observations. These might be completely stripped-off from creating real-time perspectives on an individual's emotional welfare. With modern advancements, AI-based emotion recognition powered by deep learning promises to bridge this gap. Facial Emotion Recognition (FER) is a machine learning system employed to read the facial expressions and determine the underlying emotional states FER systems can realistically collect emotional data, thus offering a nonintrusive and objective manner of mental health assessment. By means of deep learning, FER systems can make sense of the intricate facial expression patterns and predict the emotional states like happiness, sadness, anger and fear with high accuracy. Compiled and with the help of Data Analytics these insights could play an important role in the early identification of mental health issues, maybe of stress, depression or anxiety. Insert applicable funding agency, if any. If not, delete.

The significance of this system is in its ability to provide continuous monitoring and feedback in real time thereof. Mental health issues are often overlooked due to a lack of regular assessment or knowledge. Incorporating FER into everyday healthcare practices would enable patients and caretakers to get actual insights into emotional well-being that would lead to preventive care. For example, the system would bring in alerts to a responsible healthcare provider if the patient seems to display signs of being extremely stressed or depressed.

II. RELATED WORK

Emotion recognition has become a valuable tool for mental health assessment by using the advances in speech, facial expression, and multimodal data processing. Different ways have been initiated to test the possibility of improving the accuracy rate of this recognition. The MFCC and modulation spectral feature scores are cited as the best considerations for achieving a better performance in speech emotion recognition. Similarly, comprehensive surveys [5] [6] focus on the failure and successes of other conventional and deep learning ways for speech emotion recognition that are currently considered by human behavior in the provision of mental health assessments.

Emotion recognition using facial expressions has been extensively surveyed by numerous deep learning architectures previously [3]. For instance, evidence suggests that the technology can be applied proficiently in relation to the timely detection of minute changes in emotional states, driven up-to codes, prepared through mental health interventions [7].

These comprise the first steps of a long journey, the most highlighted [11] and [13]. Searches conducted at this frontier opened novel solutions that elect the differences of these available strategies to that of the emotions mounted in mental health assessment through multimodality. The use of discrete wavelet transforms with EEG for emotion recognition ([4]) is a novel research approach meant for connecting emotional states with neurophysiologic data.

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III. PROPOSED SYSTEM

The designed healthcare emotion recognition system is to change patient monitoring and mental health examination through combination of latest facial emotion recognition methods, online video processing, and powerful data management. The following subsection outlines the principal techniques used in the system in order to reach these objectives:

The five stages of the proposed work are:

1) Facial Emotion Recognition (FER).

2) Real-Time Video Processing and Monitoring.

3) Mental Health Analysis.

4) Patient Management.

5) System Architecture and User Interface.

1. Facial Emotion Recognition (FER) Using Convolutional Neural Networks (CNNs)

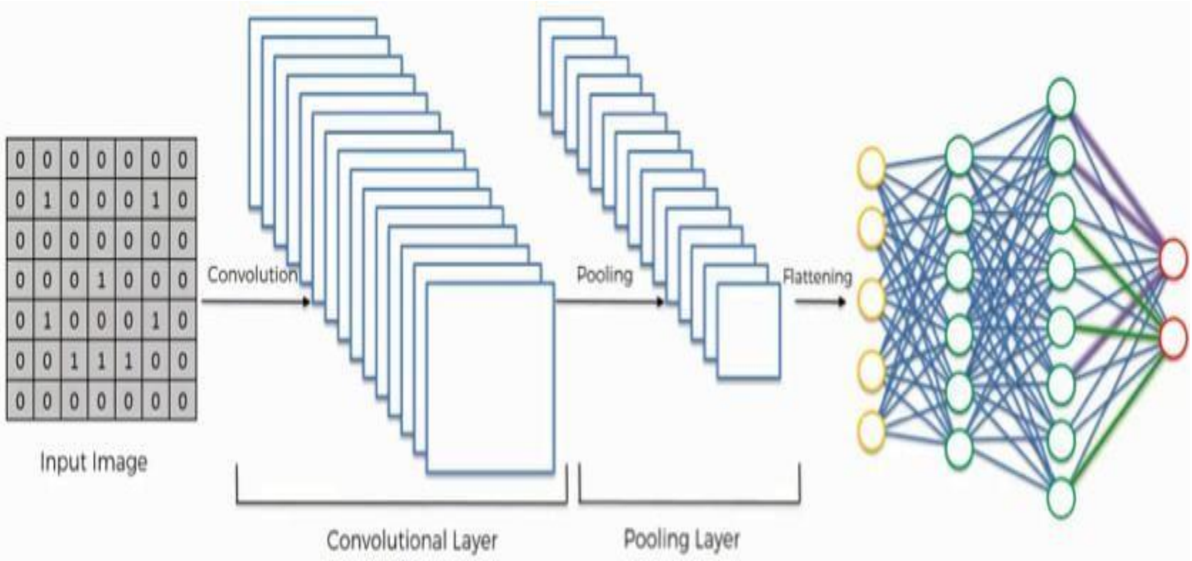

Fig. 1: CNN Architecture.

The backbone of the system is its ability to detect and classify emotions from facial expressions. This is achieved using Convolutional Neural Networks (CNNs), which are widely regarded as the most effective models for image-based tasks. The FER process involves:

- **Face Detection**:

o Live video feeds are processed frame by frame to detect faces using computer vision techniques such pre-trained models like OpenCV. Each detected face is cropped and normalized for further processing.

- **Feature Extraction**:

o The facial regions are passed through a CNN model trained on the labeled emotion dataset. The CNN extracts hierarchical features, such as edges, textures, and patterns, important for identifying emotional cues.

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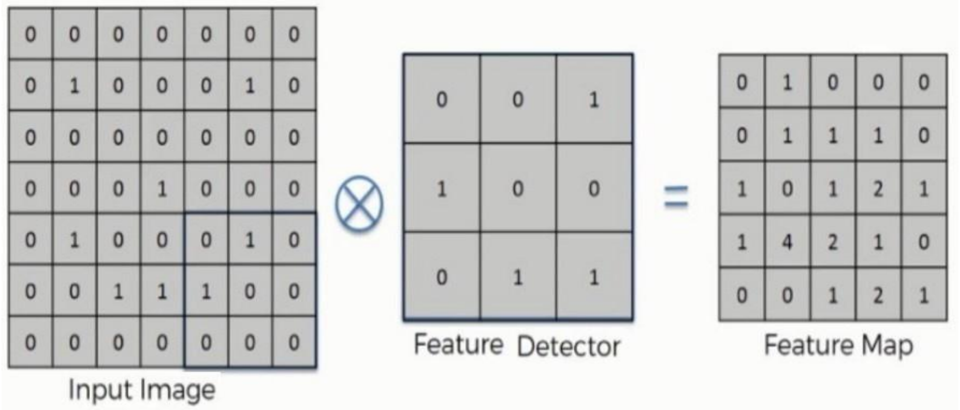

Fig. 2: Representation of feature map.

Pooling:

Pooling is a method used to decrease the size or dimensions of an image, frequently utilized in Convolutional Neural Networks. Some common pooling techniques are max, min, mean, and sum pooling. In max pooling, a 2x2 window is applied to the feature map, and the highest value within that window is chosen for the pooled feature map. Pooling helps reduce dimensions, lowers the risk of overfitting by cutting down on parameters, and enhances the model's ability to handle variations and distortions. This process boosts computational efficiency and streamlines the features that are extracted.

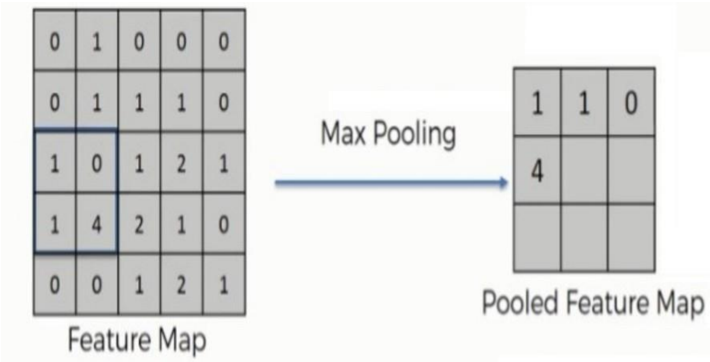

Fig. 3: Max pooling.

Flattening

The feature map obtained from pooling cannot be directly used as input for the ANN. We need to flatten the 3 x 3 pooled feature map into a single column, as illustrated in the figure.

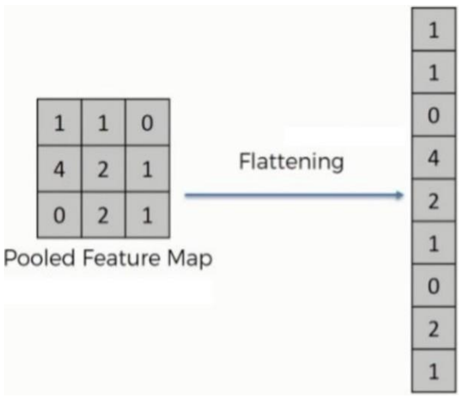

Fig. 4: Flattening.

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- **Emotion Classification**:

o The last layers of either the CNN consist of fully connected layers that are later graphed through a softmax function to classify facial expression into some predefined facial expressions like happiness, sadness, anger, fear, surprise, etc.
o For each emotion, completion of confidence scores is performed such that evaluation of predictive confidence can also be evaluated.

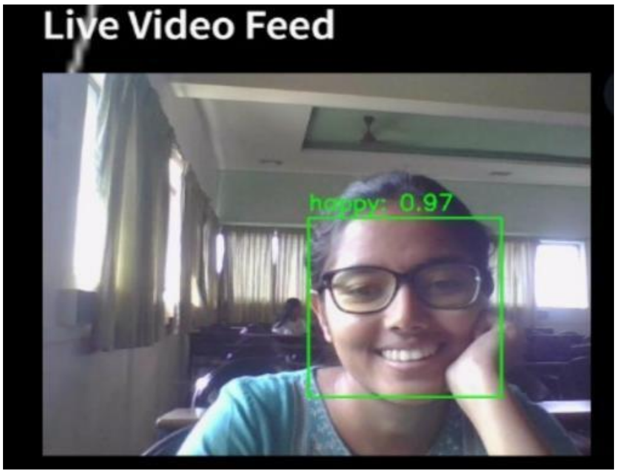
- **Pain and Distress Detection**:

o Additional custom metrics, including pain and distress levels, are calculated based on the identified emotions, allowing the system to track the patient's discomfort in real time.

2. Real-Time Video Processing and Monitoring

To provide healthcare professionals with live updates, the system includes real-time video processing capabilities. This involves:

- **Live Video Feed**:
o The system captures live video from a webcam or other camera devices and processes frames in real time.



- **Frame Processing**:

o Each frame is analysed by the FER model, which detects faces and classifies emotions. Bounding boxes are drawn around detected faces, with emotion labels shown alongside their confidence scores.

- **Database Integration**:

o Real-time emotional data include patient ID, emotional state, confidence score, pain level, and level of distress and are stored in a central database. It ensures analysis of the patient's emotional states at any given time.

3. Mental Health Analysis

Real-time emotional data include patient ID, emotional state, confidence scores, pain levels, and distress levels, which are stored in a central database. It guarantees analysis of the emotional state of the patients at all times.

- **Emotion History Analysis**:

o The system fetches the patient historical emotion data from the database and calculates the trends over time. A frequently sad or angry mood may connote, among others, depression or anxiety.

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- **Mental Health Metrics**:

o Further, depression scores, anxiety scores, and bipolar indicators are calculated from the aforementioned algorithms which analyse the emotional data. This scoring system enables the healthcare provider to establish units of measure on mental health.

- **Pattern Recognition**:

o The system employs machine learning methods to recognize patterns, which may suggest the presence of a psychological disorder. For instance, frequent shifts between happiness and sadness may suggest bipolar tendencies.

- **Visualization**:

o Emotion trends and mental health metrics are visualized through intuitive charts and graphs, enabling doctors to make informed decisions quickly.

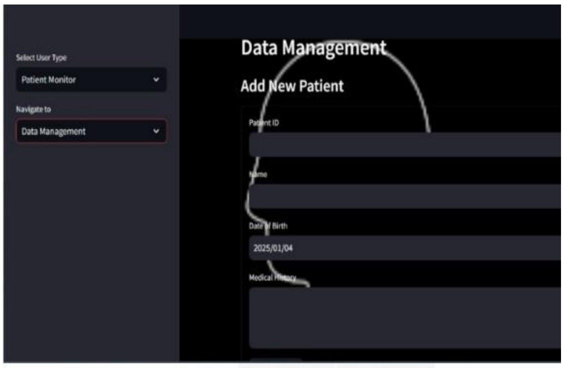
4. Patient Management

The system provides full patient management functionalities for optimizing healthcare operations. These features include::

- **Patient Registration and Management**:

o Medicine doctors are able to register patients to the system by depositing patient data, medical history and so forth.

o Existing patients can be updated or removed as needed.

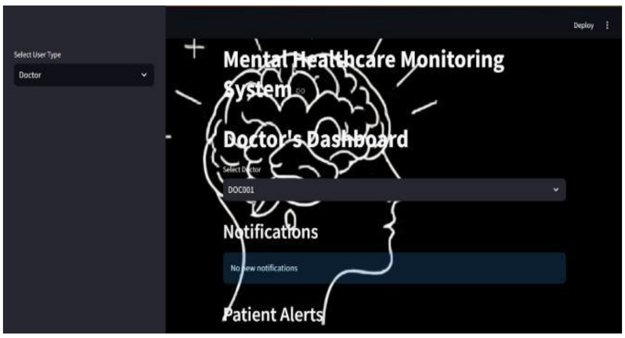


- **Data Export**:

o Emotion data and mental health analysis report can be exported in CSV format for tracing or for further analysis.

- **Alert Mechanism**:

o The system sends alarms in case emotional aberrant patterns are characterized, i.e. a long distress or a high level of anxiety. Alerts are shown on the dashboard with information about severity and timestamps.



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5. System Architecture and User Interface

The system is constructed, using Streamlit, a Python-based web application framework that offers a simple and interactive user interface.

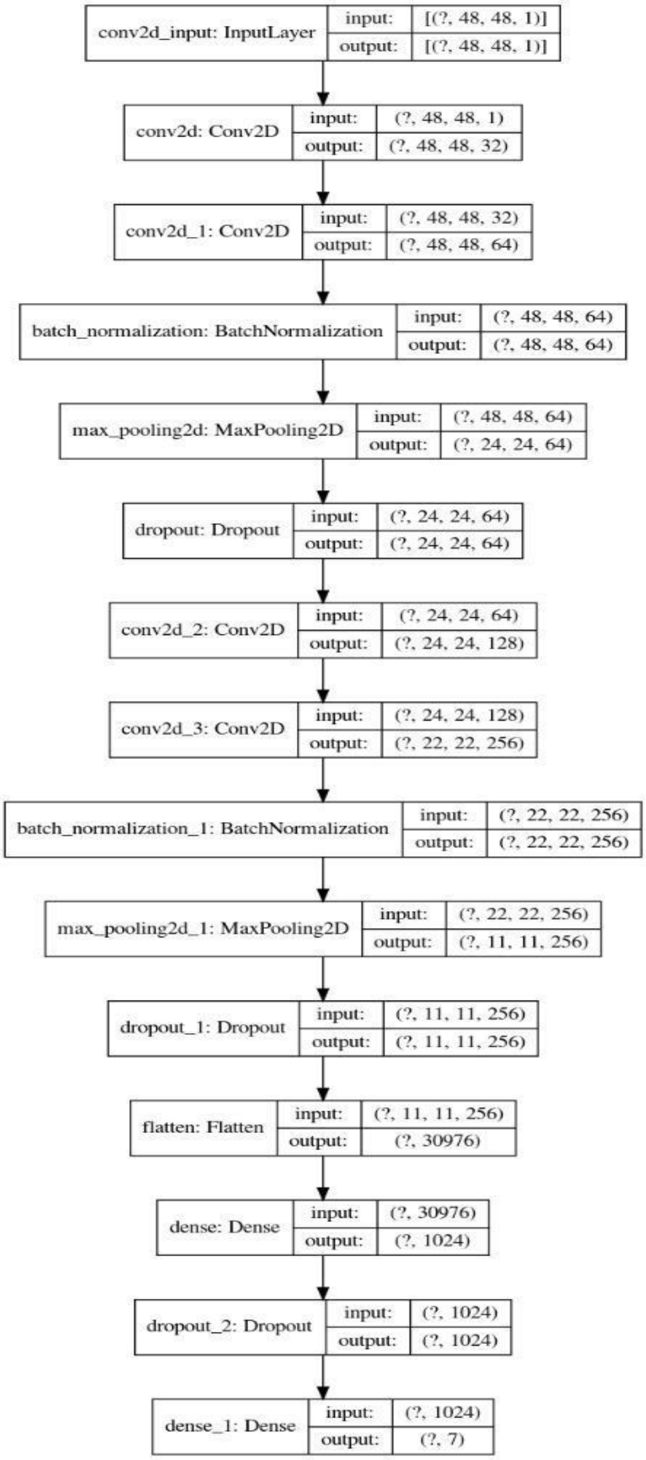

Fig. 5: System Architecture.

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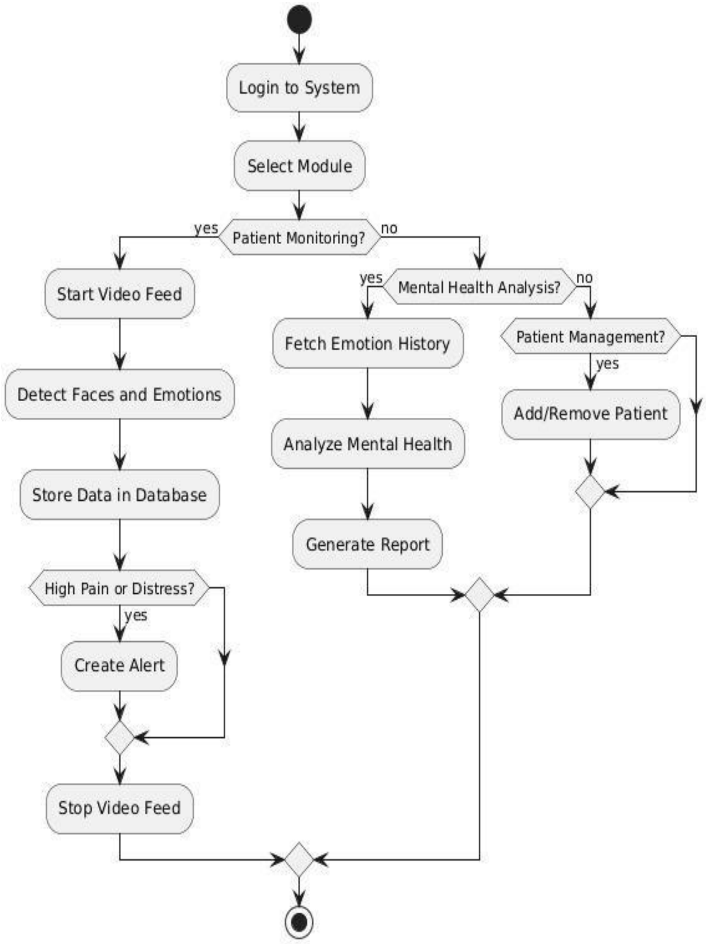

Fig. 6: Flowchart for proposed system.

- **Frontend:**

○ The ability of a Dr. to switch modules (i.e, the dashboard, patient monitoring, mental health analysis, and patient management).

- **Backend:**

○ A centralized database that stores all patient data, emotion records, and analysis results. Database queries ensure efficient data retrieval and management.

- **Integration:**

○ The integration of live video feed into FER model and database allows the system to work seamlessly.

IV. RESULTS & DISCUSSION

Here's a structured step-by-step pseudocode approach for your Healthcare Emotion Recognition (FER) project, modelled similarly to the Driver Drowsiness Detection approach:

1. Begin

2. Input Patient's Video Feed

3. Initialize emotion Data as an empty list

4. For every frame in the video do:

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- Detect Face
- Detect Emotions using the FER model
- If a face is detected:
- Record the detected emotion and confidence.
- Add the data to emotion Data.

5. If Pain Level or Distress Level is high:

- Trigger Alert for the patient.

6. If the key == "q":

- Stop the video feed and *break* the loop.

7. Analyse Emotion History:

-Calculate metrics for Depression, Anxiety, and Bipolar indicators using emotion Data.

8. Generate and Export Mental Health Report.
9. End.

- **Outputs:**

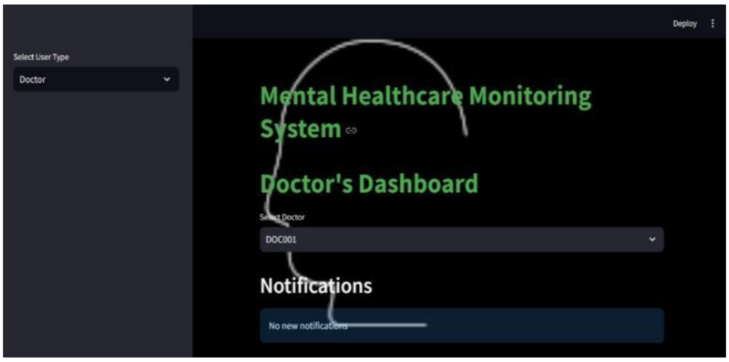

Fig 7: Doctor’s Dashboard.

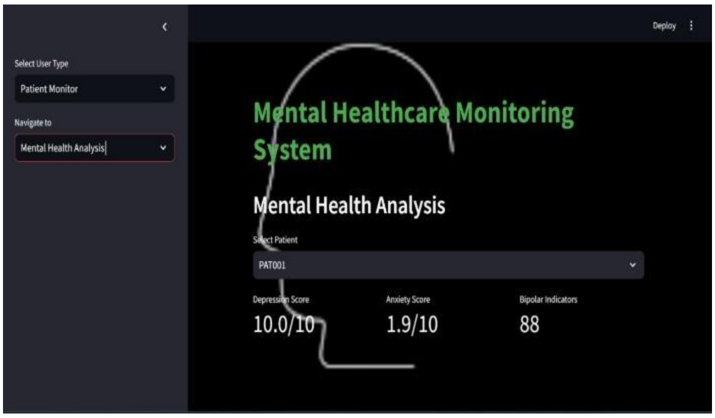

Fig 8: Mental health monitoring.

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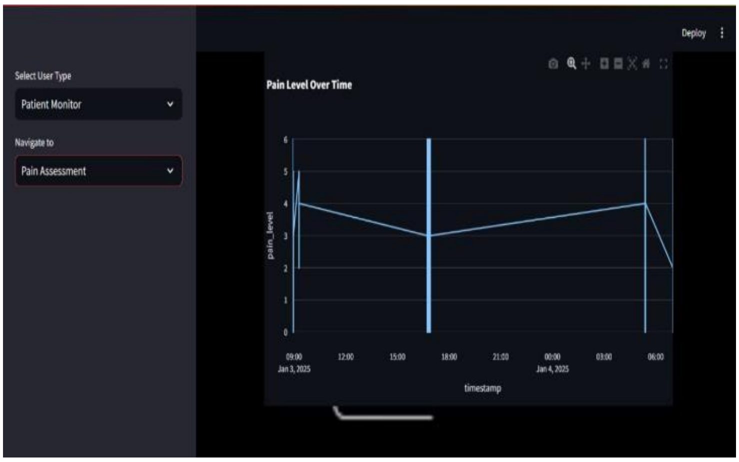

Fig 9: Pain level graph.

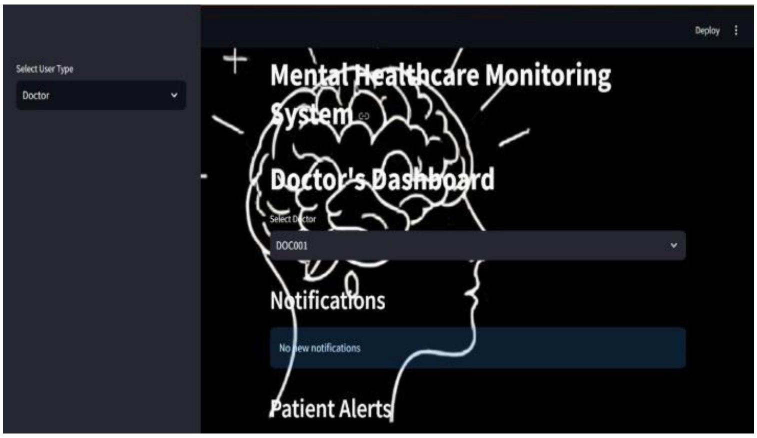

Fig 10: Patient alerts.

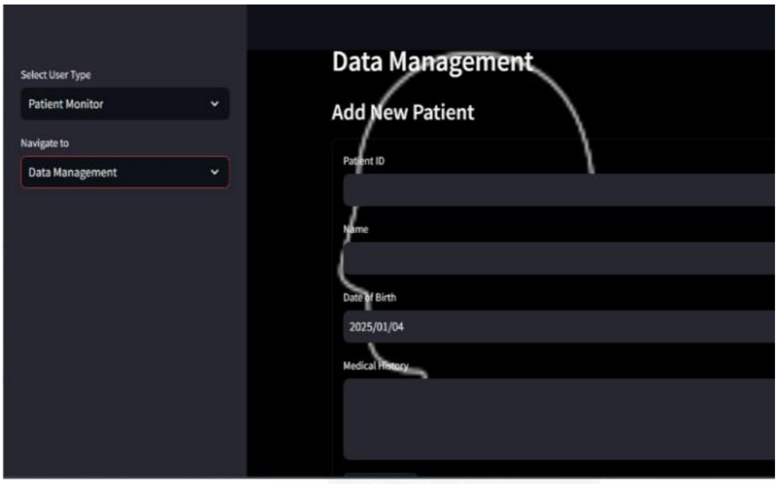

Fig 11: Patient management.

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V. CONCLUSION

This work convincingly integrates facial emotion recognition with data analytics to deliver an end-to-end solution for real-time mental health surveillance and evaluation. It enables healthcare professionals at earlier stages of the disease course to identify emotional distress, to securely manage data as it is generated, and to act sooner in order to provide personalized care. The system provides an infrastructure for the use of AI to improve mental care delivery and patient care.

TABLE I: Summary of CNN architecture

Type of the layer	#Nodes	Kernel / Filter size	Activation Function
Convolutional Layer-1	32	3	ReLU
Convolutional Layer-2	32	3	ReLU
Convolutional Layer-3	64	3	ReLU
Fully Connected Layer	128	-	ReLU
Final Layer	2	-	Softmax

TC ID	Input	Expected Output	Actual Output	Result
TC01	Video frame with a face showing **neutral** emotion	Emotion detected as **neutral**	Emotion detected as **neutral**	Pass
TC02	Video frame with a face showing **happy** emotion	Emotion detected as **happy**	Emotion detected as **happy**	Pass
TC03	Video frame with a face showing **sad** emotion	Emotion detected as **sad** and distress logged	Emotion detected as **sad** and distress logged	Pass
TC04	Video frame with a face showing **fear** emotion	Emotion detected as **fear** and alert triggered	Emotion detected as **fear** and alert triggered	Pass
TC05	Video feed with no face detected	No emotion detected	No emotion detected	Pass
TC06	Live video feed interrupted	System gracefully handles the interruption	System gracefully handles the interruption	Pass
TC07	Key q pressed during live video feed	Video feed stops	Video feed stops	Pass

TABLE II: System Testing: Test Cases (TC) for Healthcare Emotion Recognition)

The table illustrates the testing of a Healthcare Emotion Recognition system using several test cases (TCs). It assesses the accuracy of how the system identifies emotion (neutral, happy, sad, and fearful), tracks distress, and activates alarms when required. TC05 states the correct behaviour when neither face is detected, TC06 and TC07 evaluate the robustness of the system when video feed is interrupted or manually stopped. The corresponding actual outputs are always identical to the corresponding expected outputs for all cases, reflecting the robustness of the system. These tests attest to the real-time functionality of the application and robustness of the application for care emotion detection and monitoring.

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