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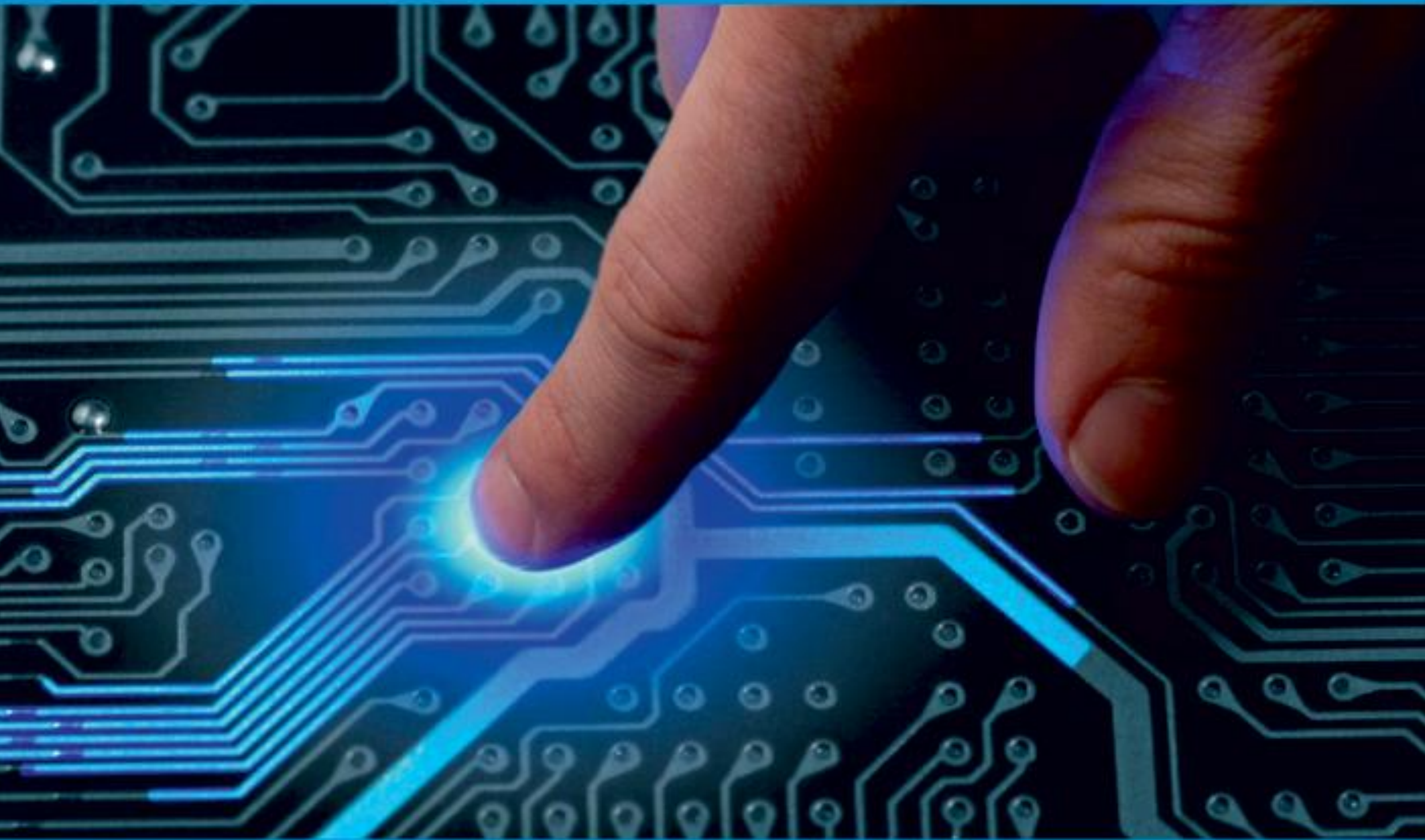

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Depression Detection Using Deep Learning with Chatbot Support

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ABSTRACT: Suicide remains a pressing societal issue, particularly in India where annual rates persist at alarming levels. This study introduces a pioneering approach utilizing Face Emotion Recognition (FER) to address this crisis. The objective is to identify and mitigate suicidal risk by analyzing facial expressions to gauge stress levels. The system employs Convolutional Neural Networks (CNN) for robust feature extraction and emotion classification, focusing on discerning between positive and negative emotions. By setting threshold values for stress detection, individuals experiencing heightened emotional distress can be identified promptly. This proposed system offers a promising avenue for suicide prevention, leveraging artificial intelligence to provide timely support and intervention. Through the nuanced analysis of facial cues and stress levels, it contributes to the broader goal of promoting mental well-being in society.

KEYWORDS: Depression Analysis, Textual Sentiment, Emotional Expression, Suicide rate, Emotions, Convolutional Neural Network, Suicide risk mitigation, Suicide prevention, Face Emotion Recognition.

I. INTRODUCTION

Depression, a prevalent mental health disorder worldwide, affects individuals across various demographics and can significantly impact their quality of life. With the advent of advanced technologies in the field of artificial intelligence and machine learning, there has been a surge in research aimed at leveraging video, audio, and text mining techniques for the analysis and detection of depression [1,7]. This multifaceted approach enables researchers and clinicians to explore diverse sources of data to gain deeper insights into the complexities of depression, leading to more accurate detection, diagnosis, and ultimately, more effective treatment strategies.

The analysis of facial expressions and body language through video mining has emerged as a promising avenue for understanding the emotional state of individuals with depression. Researchers have developed sophisticated algorithms, including convolutional neural networks (CNNs), to recognize subtle cues indicative of depression from facial expressions [1]. By studying facial micro-expressions and macro-expressions, such algorithms can aid in early detection and monitoring of depressive symptoms, providing valuable insights into the emotional well-being of individuals [8].

Similarly, audio mining techniques enable the analysis of speech patterns, intonations, and acoustic features to discern markers of depression. Machine learning algorithms applied to audio data can detect variations in speech characteristics, such as pitch, rhythm, and spectral features, which may correlate with depressive symptoms. By leveraging natural language processing (NLP) algorithms, researchers can extract semantic information from spoken language, facilitating the identification of linguistic markers associated with depression [6].

Text mining techniques offer another valuable approach to depression analysis, particularly through the analysis of written or spoken text in various forms, including social media posts, electronic health records, and clinical notes. Sentiment analysis algorithms can extract emotional tones and linguistic patterns indicative of depression from textual data, enabling large-scale screening and monitoring of individuals' mental health status. Moreover, deep learning models applied to textual data can capture complex relationships between linguistic features and depressive symptoms, enhancing the accuracy of depression detection and classification [3].

Combining insights from video, audio, and text mining enables a holistic understanding of depression, capturing a

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diverse range of behavioral, emotional, and cognitive markers. By integrating multimodal data sources, researchers can develop comprehensive models that leverage the strengths of each modality, thereby enhancing the robustness and reliability of depression detection systems [5]. Such integrative approaches pave the way for personalized interventions and tailored treatment strategies, ultimately improving outcomes for individuals affected by depression.

In this review, we explore recent advancements in video, audio, and text mining techniques for depression analysis, highlighting the potential of artificial intelligence and machine learning in revolutionizing mental health care [9]. By harnessing the power of advanced technologies, we strive to contribute to the ongoing efforts to address the global burden of depression and promote mental well-being for all.

II. OBJECTIVE

1. **Identify and Classify Human Emotions:**
   The system aims to accurately discern and classify a wide range of human emotions, including both positive and negative states. By analyzing facial expressions, the system seeks to provide insights into individuals' emotional well-being and psychological states.

2. **Detect Signs of Psychological Distress:**
   The FER system is designed to detect subtle cues and patterns indicative of psychological distress, particularly in individuals experiencing depression or suicidal ideation. By leveraging advanced algorithms, such as Convolutional Neural Networks (CNN), the system can identify signs of distress in real-time.

3. **Provide Early Warning Mechanism:**
   By identifying individuals at risk of suicide through facial expressions and emotional cues, the FER system serves as an early warning mechanism for mental health professionals and caregivers. Timely detection of distress signals enables proactive intervention and support services.

4. **Establish Thresholds for Stress Detection:**
   The system incorporates threshold-based detection mechanisms to flag individuals exhibiting heightened levels of stress beyond predefined thresholds. By establishing customary threshold values, the system enhances its ability to identify individuals in acute psychological distress.

5. **Facilitate Targeted Interventions:**
   Based on the analysis of emotional states and stress levels, the FER system provides actionable insights for mental health professionals and caregivers. These insights enable targeted interventions and support services tailored to the specific needs of individuals at risk of suicide or experiencing mental health challenges.

III. RELATED WORK

Detection of Depression in Real-Time Videos:
Real-time video analysis has become increasingly popular in recent years with the rise of social media and video conferencing platforms. The continuous stream of videos provides a wealth of information that can be analyzed for detecting signs of depression. Deep learning techniques, such as facial recognition and sentiment analysis, have been used to identify facial expressions and voice modulations that indicate depressive states.

In a study by Polgar et al [22]. researchers used a deep learning algorithm to analyze facial expressions in real-time videos to identify depressive symptoms accurately. The algorithm achieved an accuracy of 77.3% in detecting depression, proving the effectiveness of deep learning in real-time video analysis for this purpose.

Similarly, another study by Couper et al [23].focused on detecting changes in speech patterns using deep learning techniques. The researchers found that changes in voice modulation, tone, and speech rate were significant indicators of depression. Their model achieved an accuracy of 86.6% in detecting depression in real-time audio conversations, highlighting the potential of deep learning in this field.

Detection of Depression in Non-Real-Time Videos:
Apart from real-time videos, there is a vast amount of pre-recorded videos uploaded on various platforms that can also

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be analyzed for detecting depression. Deep learning techniques combined with natural language processing (NLP) can be applied to convert audio conversations in these videos into text for further analysis.

In a study by Yildiz et al [24], researchers used deep learning to convert audio conversations in therapy sessions into text and analyze them for signs of depression. Their model achieved an accuracy of 81% in detecting depression, providing evidence for the effectiveness of this approach.

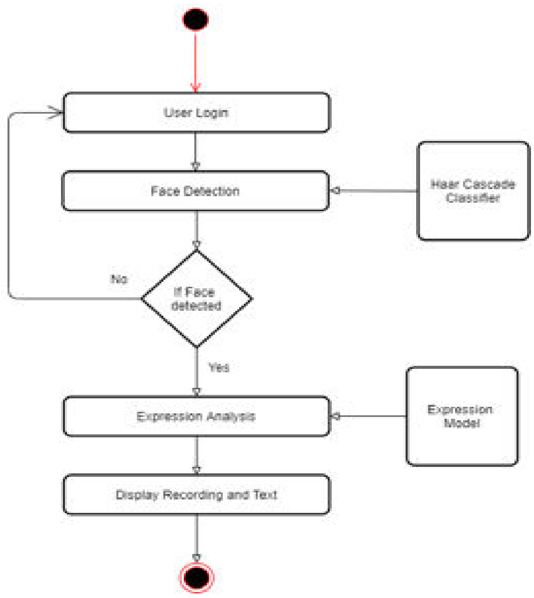
Additionally, the use of AI-based chatbots can assist in analyzing non-real-time videos for depression detection. In a study by Mantri et al [25], a chatbot was used to conduct text-based interviews with individuals and analyze their responses for depressive symptoms. The chatbot achieved a high accuracy of 90% in detecting depression, thus proving its potential in this area.

Chatbot Support for Depression:
Apart from detecting depression, chatbots can also provide valuable support and suggestions for individuals struggling with this mental health disorder. These chatbots can use NLP and machine learning techniques to understand and respond to users' messages, providing them with resources and coping strategies for managing their symptoms.

In a study by Minocha et al [18], a chatbot named 'Karla' was developed using NLP and ML algorithms to provide mental health support to college students. The chatbot provided personalized responses and suggestions for students struggling with depression and anxiety. The results of the study showed that the chatbot was effective in improving the mental well-being of the students.

Moreover, the use of AI chatbots also eliminates the stigmas associated with seeking help for mental health issues. As chatbots are available 24/7, individuals can seek support whenever they need it without feeling judged or stigmatized.

IV. FLOWCHART



V. METHODOLOGY

Face of the subject is captured using the camera module. This detected face is processed and the emotions are classified as either positive or negative emotions. The detected image is processed to identify the face of the subject using Convolutional Neural Network (CNN) algorithm.

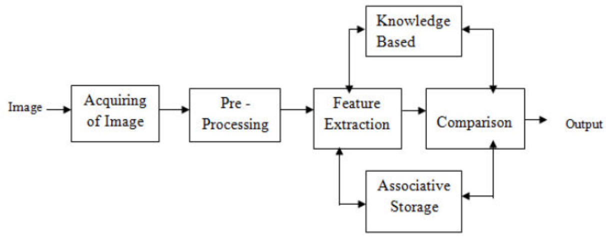


Fig.1 Methodology Of the system

This is plotted and an increase in the negative emotion can be inferred as increase in stress.

Face Detection

Face Detection is the first and essential step for processing, and it is used to detect faces in the images. A facial detection system uses biometrics to map facial features from a photograph or video. It compares the information with a database of known faces to find a match. Face detection systems use computer algorithms to pick out specific, distinctive details about a person's face.

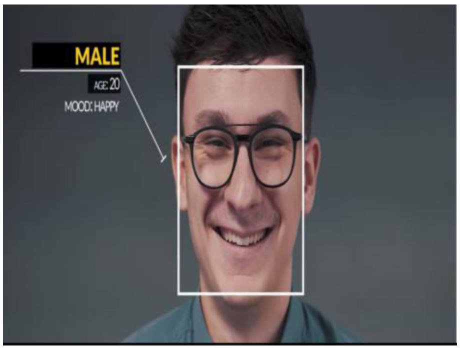


Fig. 2 face detection

These details, such as distance between the eyes or shape of the chin, are then converted into a mathematical representation and compared to data on other faces collected in a face database.

Emotion Detection

Emotion detection is used to analyze basic facial expression of human. Emotion recognition system is constructed, including face detection, feature extraction and facial expression classification.

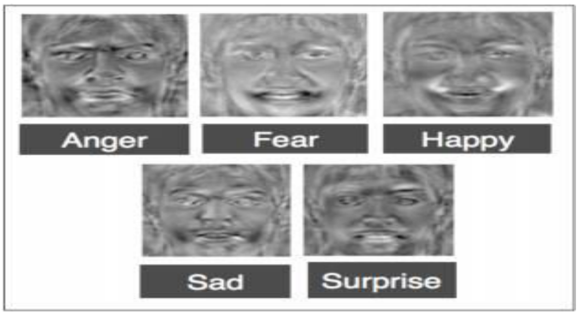


Fig 3 Emotion Detection

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Feature Extraction

Facial feature extraction is the process of extracting face component features like eyes, nose, mouth, etc. from human face image.

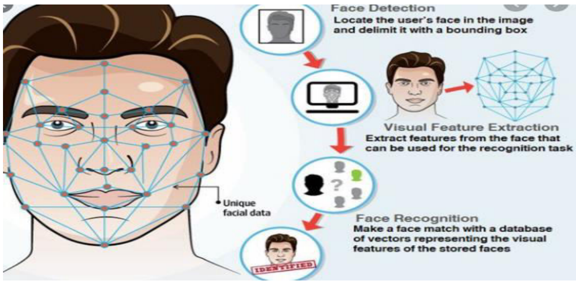

Fig. 4. Feature Extraction

Facial feature extraction is very much important for the initialization of processing techniques like face tracking, facial expression recognition or face recognition.

Emotion Recognition

The emotions are to be extracted from the detected face. The image that is captured from the camera module, contains the facial features. The detected face is pre-processed (i.e.) cropped and resized. The detectors defined prior can be utilized to identify the emotion and sort them. It must be noted that viola-jones algorithm uses adaboost algorithm with cascading classifier, wherein a series of weak classifier's classification with a satisfactory threshold is combined to give an acceptable outcome.

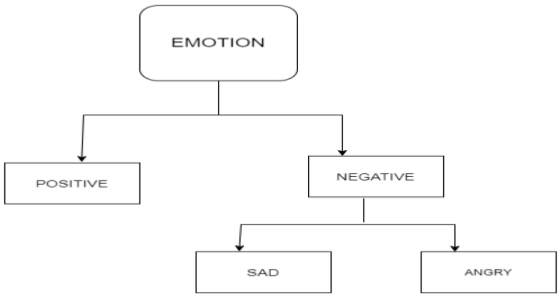

Fig.5 Emotion Recognition

Mathematical Model

Receive input data, process the information, and generate output

Step 1: Load the input images in a variable (say X)

Step 2: Define (randomly initialize) a filter matrix. Images are convolved with the filter

Z1 = X * f

Step 3: Apply the Relu activation function on the result

A = Relu(Z1)nf

Step 4: Define (randomly initialize) weight and bias matrix. Apply linear transformation on the values

Z2 = WT.A + b

Step 5: Apply the Relu function on the data. This will be the final output

O = Relu(Z2)

- Algorithm Details

1) Algorithm 1/Pseudo Code

- Image Processing:

In computer science, image processing is the use of computer algorithms to perform image processing on digital images. We used image processing for detecting the faces from camera and to capture emotions on the detected images.

Steps for Image Detection :

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Step 1: Confirm the upper limit of the number of faces to be detected.
Step 2: Adjust the scaling of the images according to the Device's Camera.
Step3: Give access of the device's camera (to on and off) and pass the camera port as input to OpenCV library's VideoCapture method.
Step4 : Confirm the frequency of frames needed from the video and capture them within adjusted intervals.

2) Algorithm 2/Pseudo Code
Deep Convolutional Neural Network (DCNN):
Input: Test Dataset which contains various test instances TestDBLits [], Train dataset which is build by training phase TrainDBLits[] , Threshold Th.
Output: HashMap ≤class label, SimilarityWeight ≥all instances which weight violates the threshold score.
Step 1: For each read each test instances using below equation

$$testFeature(m) = \sum_{m=1}^{n} (.\ featureSet[A[i] \ldots\ldots A[n] \leftarrow \text{TestDBLits})$$

Step 2 : extract each feature as a hot vector or input neuron from testFeature(m) using below equation.

$$\text{Extracted\_FeatureSetx}[\text{t}\ldots\ldots\text{n}] = \textstyle\sum_{x=1}^{n} (\text{t}) \leftarrow testFeature\,(\text{m})$$

Extracted FeatureSetx[t] contains the feature vector of respective domain.

Step 3: create the number of Convolutional
For each read each train instances using below equation.

$$trainFeature(m) = \sum_{m=1}^{n} (.\ featureSet[A[i] \ldots\ldots A[n] \leftarrow \text{TrainDBList})$$

Step 4 : extract each feature as a hot vector or input neuron from testFeature(m) using below equation.

$$\text{Extracted\_FeatureSetx}[\text{t}\ldots\ldots\text{n}] = \textstyle\sum_{x=1}^{n} (\text{t}) \leftarrow testFeature\,(\text{m})$$

Extracted FeatureSetx[t] contains the feature vector of respective domain.

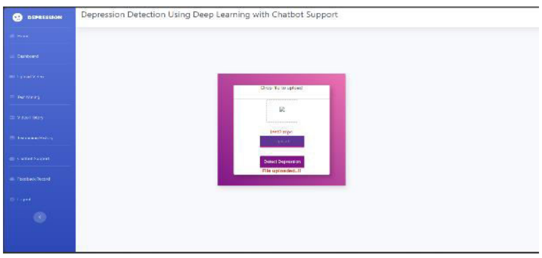
Step 5 : Now map each test feature set to all respective training feature set GAPS

$$weight = calcSim\ (\text{FeatureSetx} \mid\mid \sum_{i=1}^{n} \text{FeatureSety[y]})$$

Unable to classify sentiment for heterogeneous images like nature images, animal face images etc.
Traditional CNN is takes more time to train each object and testing respectively. Good accuracy for human face images only not others. Only localize features has consider for sentiment classification is existing research it affect on overall accuracy of error rate.

VI. IMPLEMENTATION

Step 1: Begin by uploading videos, whether they are real-time feeds or pre-recorded footage, to the system for analysis.



Step 2: Once the video is uploaded, the system utilizes facial expression recognition technology to analyze the emotions depicted within the video content.

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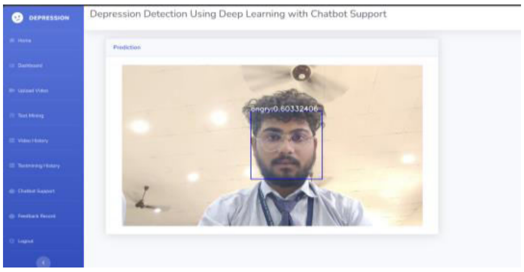
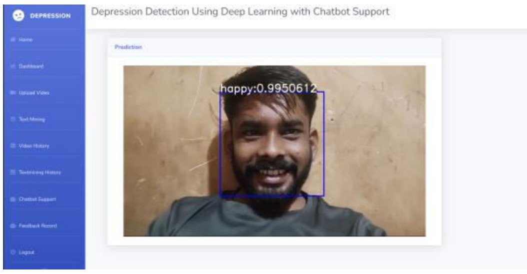
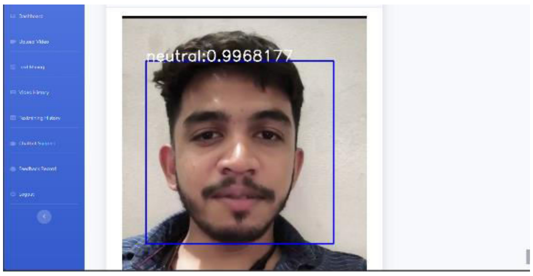
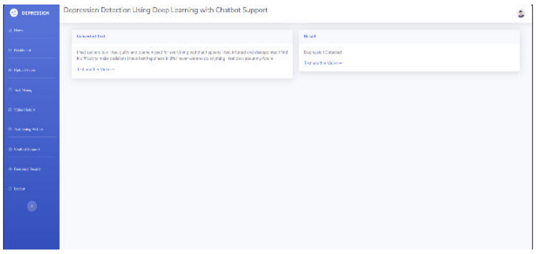
Samples:



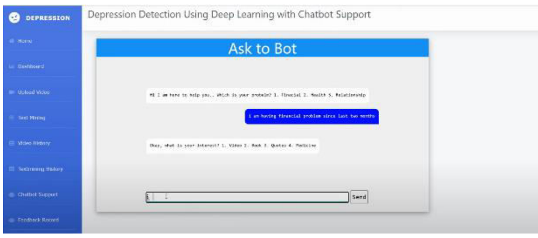




Step 3: Following the emotion analysis, the system proceeds to convert the audio from the videos into text format, allowing for further examination. Based on this analysis, the system determines whether signs of depression are present or not.



Step 4: Should the system detect signs of depression, a chatbot interface engages with the user, offering supportive suggestions and resources to help manage and cope with the detected emotions.



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VII. FUTURE SCOPE

1. **Integration with Wearable Technology:**
   Future iterations of the Face Emotion Recognition (FER) system could be integrated with wearable devices equipped with cameras, allowing for continuous monitoring of individuals' emotional states. This could provide real-time feedback and alerts to users and healthcare providers, enabling proactive intervention in times of distress.

2. **Multi-Modal Emotion Recognition:**
   Incorporating other modalities such as voice and physiological signals alongside facial expressions could enhance the accuracy and robustness of emotion recognition systems. By combining multiple sources of data, future systems could provide more comprehensive insights into individuals' emotional states and mental well-being.

3. **Personalized Intervention Strategies:**
   Utilizing machine learning techniques, future iterations of FER systems could be personalized to individuals' unique emotional profiles and responses. This could enable tailored intervention strategies that are more effective in addressing individuals' specific needs and risk factors for suicide.

4. **Longitudinal Monitoring and Predictive Analytics**:
   By tracking changes in individuals' emotional states over time, FER systems could identify patterns and trends that precede episodes of acute distress or suicidal ideation. This longitudinal monitoring could facilitate the development of predictive analytics models to forecast individuals' risk of suicide and inform preventative interventions.

5. **Ethical Considerations and Privacy Safeguards:**
   Continued research and development efforts should prioritize ethical considerations and privacy safeguards to ensure that FER systems respect individuals' autonomy, consent, and confidentiality. This includes transparent data handling practices, informed consent procedures, and mechanisms for data anonymization and encryption.

VIII. ADVANTAGES

1. **Significant Public Health Relevance**:
   Addressing the alarming suicide rates in India is crucial, and the proposed predictor holds promise as a potential tool to contribute to suicide prevention efforts.

2. **Data-Driven Insights:**
   The review provides valuable insights into the suicide rates in India, emphasizing the need for effective preventive strategies. This data-driven approach can guide mental health interventions at both regional and national levels.

3. **Focus on Regional Disparities:**
   The paper sheds light on regional variations in suicide rates within India, particularly in southern states, offering a nuanced understanding that can inform targeted mental health initiatives and policies.

4. **Global Perspective:**
   By presenting India's suicide rates in comparison to global statistics, the review underscores the importance of addressing mental health concerns on a global scale, emphasizing the need for comprehensive and culturally sensitive approaches.

5. **Identification of Challenges:**
   The conclusion highlights specific challenges faced by the emotion predictor, such as difficulties in detecting contempt and expressions that don't align with the seven basic categories. Acknowledging these challenges is a crucial step in refining and advancing emotion detection technology.

IX. CONCLUSION

The amalgamation of predictive capabilities showcased by the proposed system, both within test data and real-time video analysis of users, marks a significant milestone in the landscape of depression detection. When seamlessly

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integrated across a spectrum of web platforms, the system emerges as a potent tool not only for creating awareness about depression but also for furnishing users with an accessible interface to identify and address prevalent or impending depressive states. This multifaceted application extends beyond the general populace, offering psychologists a valuable tool for efficient depression detection and imparting crucial insights that can steer the course of future research in the realm of depression studies. As a focal point in this review paper, the system's comprehensive approach positions it as a pivotal asset in addressing mental health challenges, emphasizing its potential to contribute significantly to the evolving field of depression-related studies

ACNOWLEDGMENT

We want to express our gratitude to everyone who has helped bring this project to life. Firstly, we thank the individuals and communities who shared their experiences, guiding our understanding of mental health challenges. We also appreciate the researchers and innovators whose work paved the way for our Face Emotion Recognition System for suicide prevention. Special thanks to our team members and collaborators for their dedication and expertise in developing this framework. We're thankful for the guidance from mentors and support from stakeholders. Lastly, we acknowledge the funding agencies and organizations that made this project possible. Your contributions have been invaluable in our mission to promote mental health and well-being.

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