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DEVELOPING A PERSONALISED MENTAL HEALTH ASSISTANT USING AI

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ABSTRACT:

Emotion-based mental health prediction using chatbots, powered by the Haar Cascade algorithm, represents an innovative approach to mental health care through real-time emotional analysis and prediction. This system leverages computer vision techniques alongside artificial intelligence (AI) to capture and analyze users' facial expressions and emotions during interactions with the chatbot. By incorporating the Haar Cascade algorithm, which is widely used for object detection, particularly face detection, the system can identify key facial features that correlate with emotional states such as happiness, sadness, anger, and anxiety.The chatbot functions by using a camera to detect and track the user's face in real time. The Haar Cascade algorithm processes these visual inputs to recognize patterns in facial features and expressions. This data, combined with natural language processing (NLP) for analyzing user text input, allows the chatbot to assess the emotional state of the user accurately. Based on these emotional cues, the system makes predictions about the user's mental health, identifying potential signs of stress, depression, or other psychological conditions. The chatbot then provides appropriate recommendations or resources to support the user's mental well-being.This paper focuses on the integration of the Haar Cascade algorithm for emotion detection in mental health prediction chatbots. It examines the methodology behind facial feature extraction, emotional classification, and the predictive model for mental health assessment.

1. INTRODUCTION

The increasing prevalence of mental health issues worldwide has led to a growing demand for accessible, real-time mental health support. Traditional mental health services often involve in-person consultations and assessments, which can be time-consuming and limited in availability. In response, AI-powered chatbots have emerged as an innovative solution, providing users with continuous and personalized support. By integrating emotion detection, these chatbots can go beyond simple conversation and delve into the user's emotional well-being, making real-time predictions about their mental health.

The integration of the Haar Cascade algorithm in an emotion-based mental health prediction chatbot allows for a multimodal analysis—combining facial expression detection with natural language processing (NLP) to assess both verbal and non-verbal emotional cues. This hybrid approach provides a more comprehensive understanding of the user's emotional state, enabling the chatbot to make more accurate predictions about potential mental health conditions like depression, anxiety, or stress. The chatbot can then offer timely support by recommending relaxation techniques, therapy resources, or guiding the user toward seeking professional help.

Facial expression recognition is the process of identifying human emotion based on facial expressions. Humans are naturally capable of recognizing emotions. In fact, children, who are only 36 hours old, can interpret some very basic emotions from their faces. In older humans, this ability is considered one of the most important social skills. There is a universality in facial expressions of humans in expressing certain emotions. Humans develop similar muscular movements belonging to a certain mental state, despite their place of birth, race, education, etcetera. Therefore, if properly being modelled, this universality can be a convenient feature in human-machine interaction: a well-trained system can understand emotions, independent of who the subject is.One of the key technologies enabling emotion detection is the Haar Cascade algorithm, a computer vision technique primarily used for object and facial feature detection. Developed by Paul Viola and Michael Jones, this algorithm uses a cascade of classifiers to detect patterns in images, making it highly effective for real-time face and emotion recognition. When applied to mental health prediction, the chatbot uses the Haar Cascade algorithm to analyze the user's facial expressions during interaction, identifying key features that correlate with different emotional states, such as happiness, sadness, anger, or anxiety.

2. LITERATURE SURVEY:

Several studies highlight the effectiveness of AI-driven chatbots in delivering mental health support. Chatbots such as Woebot and Wysa have been successful in providing conversational therapy, relying on NLP to detect emotional cues from text. These chatbots use machine learning algorithms to analyze users' input, helping to identify early signs of mental health conditions like anxiety and depression

Emotion recognition through facial expressions has been a focus in the AI community, particularly using algorithms like the Haar Cascade. Research has shown that facial expressions are reliable indicators of emotions, and their integration into mental health systems can improve the accuracy of emotional assessments (Tarnowski et al., 2017). This has led to the development of multimodal systems that analyze both text and visual data for a holistic approach to emotion-based mental health prediction

Sentiment analysis is a well-researched area in NLP and has been employed extensively in mental health chatbots. Sentiment analysis algorithms can detect underlying emotional tones in text, such as positive, neutral, or negative sentiments. Studies show that sentiment analysis, when combined with emotion recognition, significantly improves the chatbot's ability to predict mental health conditions.

This work explores facial expression bias as a security vulnerability of face recognition systems. Despite the great performance achieved by state-of-the-art face recognition systems, the algorithms are still sensitive to a large range of covariates. We present a comprehensive analysis of how facial expression bias impacts the performance of face recognition technologies. Our study analyzes: i) facial expression biases in the most popular face recognition databases; and ii) the impact of facial expression in face recognition performances. Our experimental framework includes two face detectors, three face recognition models, and three different databases. Our results demonstrate a huge facial expression bias in the most widely used databases, as well as a related impact of face expression in the performance of state-of-the-art algorithms. This work opens the door to new research lines focused on mitigating the observed vulnerability.

The Haar Cascade algorithm is widely used for detecting facial features, and researchers have applied it in mental health systems to identify emotions such as happiness, sadness, anger, or fear. By recognizing facial landmarks, this algorithm provides real-time analysis of the user's emotional state. Studies emphasize its efficiency in detecting facial expressions, though accuracy can be limited by lighting conditions and camera quality

In the current study, we investigated whether emotion recognition, assessed by a validated emotion recognition task, is impaired for faces wearing a mask compared to uncovered faces, in a sample of 790 participants between 18 and 89 years (condition mask vs. original). In two more samples of 395 and 388 participants between 18 and 70 years, we assessed emotion recognition performance for faces that are occluded by something other than a mask, i.e., a bubble as well as only showing the upper part of the faces (condition half vs. bubble). Additionally, perception of threat for faces with and without occlusion was assessed. We found impaired emotion recognition for faces wearing a mask compared to faces without mask, for all emotions tested (anger, fear, happiness, sadness, disgust, neutral). Further, we observed that perception of threat was altered for faces wearing a mask. Upon comparison of the different types of occlusion, we found that, for most emotions and especially for disgust, there seems to be an effect that can be ascribed to the face mask specifically, both for emotion recognition performance and perception of threat.

AI-based mental health chatbots have been widely explored due to their potential to offer continuous emotional support and counseling services. Studies like those of Fitzpatrick et al. (2017) have shown that chatbots can provide effective cognitive-behavioral therapy through text-based interactions, often identifying early signs of mental health issues by analyzing user responses.

Sentiment analysis, a subfield of NLP, is a key technology for identifying emotional states in text-based interactions. Research by Schuller et al. **(2013)** shows that sentiment analysis can detect positive, neutral, and negative emotions from text, which helps in predicting mental health conditions. The accuracy of such predictions is enhanced when sentiment analysis is combined with context-aware NLP techniques.

Multimodal systems that incorporate both text (NLP) and image (facial recognition) data have been identified as more effective in emotion detection. Studies like Hernández et al. **(2019)** demonstrate that combining text-based sentiment analysis with facial recognition yields better emotional predictions, allowing for more accurate mental health assessments.

The Haar Cascade algorithm, widely used for real-time facial detection, plays a significant role in emotion-based mental health chatbots. This algorithm, developed by Viola and Jones (2001), is a machine learning object detection algorithm that can detect faces and facial features with high efficiency. Emotion detection through facial expressions has been studied extensively, and it has been found that facial expressions provide vital non-verbal cues about a user's emotional state .

3. METHODOLOGY

3.1 DATA COLLECTION AND PREPROCESSING

The dataset is divided into training sets and test sets. Each sample represents a traffic sign labeled as one of 2 classes. The shape of a traffic sign image is scaled to 256×256 pixels in 3 channel RGB representation. Below, there are a few random samples from the dataset: viol jones images are collected.

Variations that are irrelevant to facial expressions, such as different backgrounds, illuminations and head poses, are fairly common in unconstrained scenarios. Therefore, before training the deep neural network to learn meaningful features, pre-processing is required to align and normalize the visual semantic information conveyed by the face Illumination and contrast can vary in different images even from the same person with the same expression, especially in unconstrained environments, which can result in large intra-class variances Image size

3.2 PROPOSED SYSTEM

A proposed system for Emotional Detection of Mental Health Using a Chatbot incorporating the Haar Cascade Algorithm focuses on improving emotion detection by utilizing facial expression analysis, alongside text-based sentiment analysis. Haar Cascade, traditionally used for object detection (such as face detection), can be adapted to recognize facial expressions that reflect the user's emotional state, enhancing the chatbot's ability to provide personalized mental health support. The proposed system integrates both text-based sentiment analysis and facial expression recognition using the Haar Cascade Algorithm to better assess the user's emotional state. By analyzing both text and visual data (facial expressions), the system can make more accurate predictions about the user's emotions, leading to more appropriate and timely mental health interventions. The system applies NLP techniques to analyze user input and detect emotions based on the tone and context of the conversation. It uses tokenization, lemmatization, and sentiment analysis to understand the emotional content of the text. After processing the text, a machine learning model (such as a Support Vector Machine or a neural network) is used to classify emotions into categories like happy, sad, anxious, or neutral based on linguistic features. This provides the first layer of emotional detection.

3.4 ALGORITHM

The Haar Cascade Algorithm works by detecting objects in images or video streams using Haar-like features, which are simple rectangular features that calculate the intensity difference between adjacent regions of an image. These features are used to differentiate between object and non-object regions, such as detecting the eyes, nose, and mouth in a face.

3.4.1 HAAR CASCADE EXTENSIONS

Haar Cascade Extensions refer to various improvements and adaptations made to the original Haar Cascade Algorithm introduced by Paul Viola and Michael Jones. These extensions enhance the performance, accuracy, and applicability of the algorithm for more advanced or specific object detection tasks.

The Local Binary Pattern (LBP) algorithm is an extension of Haar Cascade that uses LBP features instead of Haar-like features to detect objects. LBP works by comparing each pixel to its neighboring pixels and creating a binary pattern based on the intensity difference.The integration of deep learning with the cascade approach has led to the development of deep cascade networks. Instead of relying on manually designed Haar-like features, this extension uses convolutional neural networks (CNNs) to automatically learn and extract features from images.

These layers perform operations that alter the data with the intent of learning features specific to the data. Three of the most common layers are: convolution, activation or ReLU, and pooling.

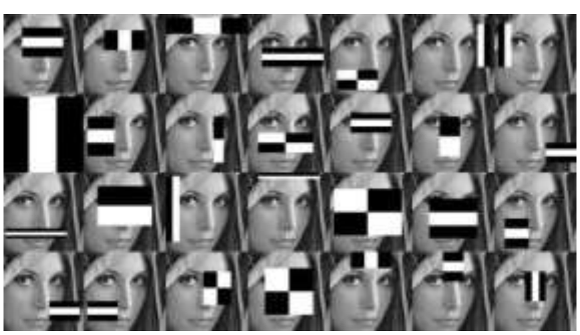

Fig 1: Haar cascade

Making a Haar Cascade Classifier

This discussion will assume basic knowledge of boosting algorithms and weak vs. strong learners with regards to machine learning. The algorithm can be explained in four stages:

- Calculating Haar Features
- Creating Integral Images
- Using Adaboost
- Implementing Cascading Classifiers

It’s important to remember that this algorithm requires a lot of positive images of faces and negative images of non-faces to train the classifier, similar to other machine learning models.

Calculating Haar Features

The first step is to collect the Haar features. A Haar feature is essentially calculations that are performed on adjacent rectangular regions at a specific location in a detection window. The calculation involves summing the pixel intensities in each region and calculating the differences between the sums.

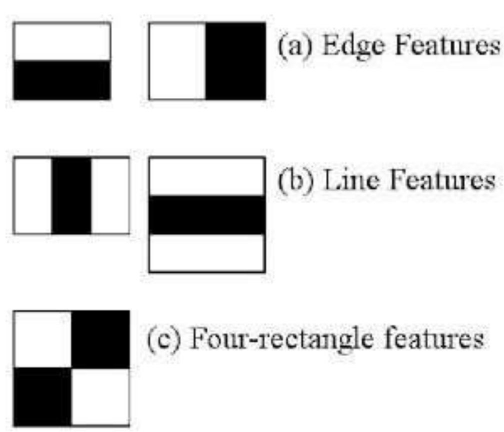

Fig 2 : Examples of Haar features

These features can be difficult to determine for a large image. This is where integral images come into play because the number of operations is reduced using the integral image.

Creating Integral Images

Without going into too much of the mathematics behind it (check out the paper if you're interested in that), integral images essentially speed up the calculation of these Haar features. Instead of computing at every pixel, it instead creates sub-rectangles and creates array references for each of those sub-rectangles. These are then used to compute the Haar features.

The cascade classifier is made up of a series of stages, where each stage is a collection of weak learners. Weak learners are trained using boosting, which allows for a highly accurate classifier from the mean prediction of all weak learners.based on this prediction, the classifier either decides to indicate an object was found (positive) or move on to the next region (negative). Stages are designed to reject negative samples as fast as possible, because a majority of the windows do not contain anything of interest.It's important to maximize a low false negative rate, because classifying an object as a non-object will severely impair your object detection algorithm. A video below shows Haar cascades in action. The red boxes denote "positives" from the weak learners.

3.3 SYSTEM ARCHITECTURE

A system architecture is the conceptual model that defines the structure, behavior, and more views of a system. An architecture description is a formal description and representation of a system, organized in a way that supports reasoning about the structures and behaviors of the system.

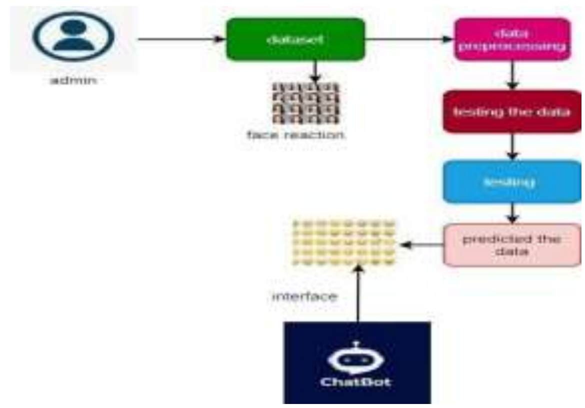

Fig 3: System architecture

3.5 PERFORMANCE EVALUATION:

The performance evaluation of the emotion-based mental health prediction system using chatbots revolves around specific metrics and comparisons with other algorithms. The system uses metrics like accuracy to measure the correct classification of emotional states, precision to evaluate the correctness of identified emotions relative to all identified cases, and recall (sensitivity) to assess the system's ability to identify all relevant emotional states. Additionally, the F1 score is employed to balance precision and recall, providing a comprehensive measure of effectiveness, while latency is analyzed to determine the system's responsiveness in real-time emotion recognition.

3.5.1 COMPARISON WITH OTHER ALGORITHMS:

When compared to other algorithms, the Haar Cascade algorithm demonstrates distinct strengths and limitations. Against deep learning models like Convolutional Neural Networks (CNNs), Haar Cascade is faster and more efficient for real-time detection but tends to be less accurate in scenarios involving poor lighting or unconventional angles. CNNs, on the other hand, provide higher accuracy and robustness in diverse environments but require significant computational resources and processing time. Compared to Local Binary Patterns (LBP), Haar Cascade handles larger datasets with lower computational demand, although LBP slightly outperforms in identifying finer emotional details but at the cost of slower performance. In contrast with sentiment analysis using Natural Language Processing (NLP), Haar Cascade focuses on non-verbal cues like facial expressions, whereas sentiment analysis interprets verbal inputs for emotion detection. Combining both approaches, as done in this system, enhances overall performance by leveraging the strengths of both modalities.

By integrating Haar Cascade for visual emotion detection with NLP for analyzing textual inputs, the system achieves a balance between speed and accuracy, enabling effective real-time mental health prediction and support. This multimodal approach ensures robust emotion detection across varied scenarios, making it a reliable tool for mental health assessment and intervention.

4. USE CASE :

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

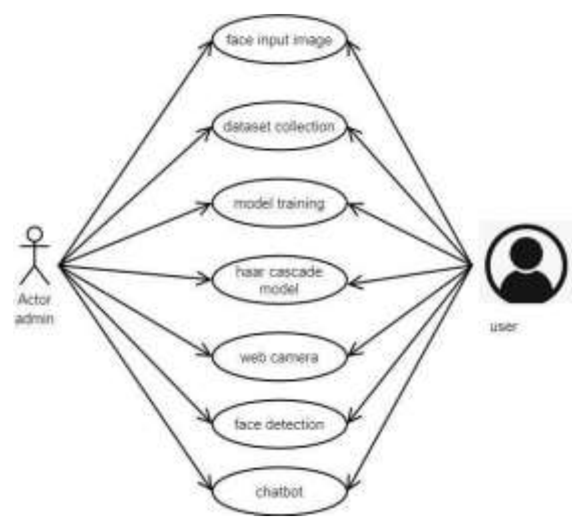

Fig 4 : Use case diagram

5. EXPERIMENTAL RESULTS:

Fig 5 : Neutral face

Fig 6: Sad face

Fig 7 : Surprise face

6. CONCLUSION:

The integration of emotional detection in mental health chatbots represents a significant advancement in the field of mental health support. By utilizing various techniques such as text sentiment analysis, facial emotion recognition, and the fusion of these modalities, chatbots can provide more personalized and empathetic interactions. This not only enhances user engagement but also helps in identifying users' emotional states more accurately. The emotional detection capabilities of the chatbot facilitate timely and relevant responses, allowing users to feel understood and supported.Moreover, the potential for continuous learning and adaptation enables these systems to improve over time, making them more effective in addressing the evolving needs of users. While challenges such as privacy concerns and the need for accurate emotion recognition persist, the development of such systems holds promise for providing accessible mental health support, reducing the stigma around mental health issues, and promoting overall well-being.In conclusion, emotional detection in chatbots can play a pivotal role in enhancing mental health services, providing users with timely support, and fostering a greater understanding of their emotional needs.

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