

Augmenting Sentiments into Chat-GPT using Facial Emotion Recognition

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Abstract—This research initiative addresses the task of enhancing ChatGPT’s conversational capabilities by integrating the comprehension and response to user emotions conveyed through facial expressions. The central challenge lies in refining the AI system’s proficiency to tailor responses according to users’ detected emotional states. In this pursuit, our study adopts a comprehensive approach, aiming to seamlessly incorporate emotional intelligence into AI-driven interactions.

To achieve this objective, the methodology involves integrating real-time sentiment analysis based on facial expressions into the ChatGPT framework. This is carried out through the utilization of a deep convolutional neural network (DCNN) architecture, designed to recognize and interpret various emotions exhibited in facial expressions. The primary goal is to enable ChatGPT to dynamically adjust its responses, fostering a more empathetic and contextually relevant interaction with users.

In terms of evaluation metrics for facial expression recognition, our assessment employs a confusion matrix to quantify the model’s performance across different emotional categories. Additionally, a heuristic approach is implemented, wherein the sum total probability of each detected emotion is calculated over the duration the user enters the prompt. These evaluation methodologies aim to provide a comprehensive understanding of the model’s accuracy and effectiveness in discerning and responding to user emotions. Overall, this research contributes to the ongoing endeavor of imbuing AI systems with emotional intelligence, paving the way for more nuanced and human-like interactions.

Index Terms—Fine-tuning, Natural Language Processing, Sentiment Analysis, Transformer, Machine Learning, GPT

I. INTRODUCTION

Human-computer interaction has advanced significantly in the current digital era, and artificial intelligence (AI) is already a crucial aspect of our everyday existence. Artificial intelligence (AI)-powered devices, including chatbots and virtual assistants, are becoming increasingly commonplace and are revolutionising communication and information access. But a crucial component of human communication that is frequently absent from these exchanges is the comprehension of emotions. Effective communication is essential to having more meaningful and sympathetic connections with others. It involves being aware of and sensitive to human emotions.

Affective computing, a branch of AI, focuses on imbuing machines with the ability to comprehend and respond to human emotions. This field has garnered significant attention due to its potential in enhancing user experience, particularly

in conversational AI. Sentiment analysis, a key component of affective computing, involves the identification and interpretation of emotions expressed by users. Traditional methods of sentiment analysis rely on textual data, but the richness of human emotions extends beyond words. Facial expressions serve as a potent non-verbal cue, reflecting a person’s emotional state vividly.

In this research endeavor, we delve into the integration of real-time sentiment analysis based on facial expressions within conversational AI systems. Our approach combines deep learning techniques and computer vision to capture and interpret facial cues, enabling AI models to adapt their responses according to the user’s emotional state. The proposed deep convolutional neural network (DCNN) architecture inspired by [5] and [4] forms the backbone of our methodology. This architecture is designed to process facial images and extract meaningful features that signify various emotions.

The core objective of this study is to bridge the gap between human emotions and AI interactions. By integrating facial expression analysis seamlessly into AI systems, we aim to create a more empathetic and contextually aware conversational experience.

The integration of real-time sentiment analysis based on facial expressions in conversational AI marks a significant stride toward human-like interactions with machines as taken in [1]. This research not only advances the technological landscape but also has profound implications for various domains, including customer service, mental health support, and human-computer collaboration. In the following sections, we provide a detailed account of our methodology, experimental setup, results, and implications, shedding light on the transformative potential of this interdisciplinary research endeavor.

This overarching problem can be broken down into three distinct, This study centers around three critical research questions:

A. Sub-Problem 1: Facial Expression Recognition

Efficiently recognizing and accurately interpreting real-time facial expressions to identify users’ emotional states, involving the creation of robust computer vision models. We have utilized an approach similar to [3] for our pipeline.

B. Sub-Problem 2: Integration of Sentiment Data

Developing an effective method to seamlessly incorporate sentiment data, obtained from facial expression analysis, into the ChatGPT prompt while maintaining contextual coherence.

C. Sub-Problem 3: Sentiment-Aware Response Generation

Adapting ChatGPT’s response generation algorithm to consider detected user emotions and generate responses that are contextually relevant and empathetic, thereby enhancing the overall user experience.

II. RELATED WORK

Traditionally, facial expression recognition algorithms have been based on laboratory-collected datasets like FER13, CK+, and JAFFE. However, in chaotic or uncontrolled situations, their efficacy can be diminished. In an attempt to close this gap, recent attempts have introduced datasets created especially for wild scenarios, as contributions [2]–[6] serve as examples. There are still difficulties in identifying facial expressions from natural data, especially when it comes to non-frontal and partially covered faces.

RAF-ML, a real-world facial expression database designed to overcome obstacles in extreme situations, was introduced by Shan Li et al. [6]. By employing a DeepBi-Manifold (DBM) methodology, RAF-ML exhibits similar performance in comparisons across different databases. Its various features allow RAF-ML to be a flexible ‘generic’ database for training facial expression analysis models.

XIA et al. [7] used the Inception-v3 model in TensorFlow in a different study, proving that a successful facial recognition model is feasible. Retraining Inceptionv3 with facial data as part of their transfer learning technique successfully shortened the training period.

While CNN-based techniques have shown to be especially successful for image classification-based applications, hand-crafted and automated feature extraction through deep learning are also recognised ways for Facial Expression Recognition (FER) [8]. Conventional CNN architectures have continuously produced state-of-the-art results in FER, highlighting their applicability for many FER scenarios [8].

Previous studies have mostly employed lab-controlled datasets to identify seven fundamental emotions, which has resulted in FER solutions that are more widely applicable but less robust. Acknowledging this drawback, attempts have been undertaken to develop a reliable real-world FER system that can identify particular fundamental facial expressions in a range of settings. By accurately recognising fundamental human emotions on current lab-controlled and wild datasets, our suggested deep learning methodology hopes to further the creation of effective FER systems. The references are [9], [10], [11], [12], and [13].

III. METHODOLOGY

A. Data Collection and Preprocessing

We made use of the open-source AffectNet dataset, which is available to the general public and contains over a million

facial photos labelled with seven main emotional classes: disgust, anger, fear, happy, sad, surprise, and neutral. A wide range of emotions and facial expressions from people in different groups are captured in this diversified dataset. We selected a subset of 100,000 photos for our study in order to guarantee that each emotional category was fairly represented. We train and evaluate our model using these photos as the foundation. We ensured uniform resolution by standardizing the photos to a consistent format before preparing the data. Additionally, we used data augmentation methods including flipping and rotation to improve the dataset’s quality and the model’s capacity to generalize across various facial positions.

Mathematically, the preprocessing steps inspired by the work in [14], [15] and [16] can be represented as follows:

$$\begin{aligned} X_{\text{std}} &= \frac{X - \mu}{\sigma} \\ X_{\text{rotated}} &= \text{rotate}(X, \theta) \\ X_{\text{flipped}} &= \text{flip}(X) \end{aligned}$$

Where X_{std} represents the standardized image, X denotes the original image, μ is the mean pixel value, σ is the standard deviation of pixel values, θ is the rotation angle, X_{rotated} is the rotated image, and X_{flipped} is the flipped image.

B. Deep CNN Architecture

To create our deep convolutional neural network (CNN) model, we followed a step-by-step process as described below. The model was implemented using the Keras framework.

1) *Data Preprocessing*: We began by loading the dataset from a CSV file, which contains facial expression data. We split the data into training and testing sets based on the ‘Usage’ column. The ‘pixels’ column was processed to extract the numerical values, which represent facial expressions.

2) *Model Parameters*: We defined several key parameters for our model, including the number of features, the number of labels (emotions), batch size, the number of training epochs, and the image dimensions (width and height).

3) *Data Normalization*: To ensure that the data is appropriately scaled, we normalized it between 0 and 1. This step involved subtracting the mean and dividing by the standard deviation of the data for both the training and testing sets.

4) *Convolutional Neural Network Architecture*: Our CNN model consists of several layers, including convolutional layers, max-pooling layers, and fully connected layers. Here is a summary of the architecture:

- 1) **1st Convolution Layer**: We added a convolutional layer with 64 filters and a 3x3 kernel. ReLU activation was applied. Another identical convolutional layer followed. A max-pooling layer with a 2x2 pool size and 0.5 dropout was included.
- 2) **2nd Convolution Layer**: Similar to the first, we added two convolutional layers with 64 filters, ReLU activation, and a max-pooling layer with dropout.
- 3) **3rd Convolution Layer**: We introduced two convolutional layers with 128 filters, ReLU activation, and a max-pooling layer.

- 4) **Flatten Layer:** Following the convolutional layers, we flattened the output to prepare for the fully connected layers.
- 5) **Fully Connected Layers:** We included two fully connected layers with 1024 neurons and ReLU activation. A dropout of 0.2 was applied after each fully connected layer.
- 6) **Output Layer:** The final layer is the output layer with the number of neurons equal to the number of emotion labels. Softmax activation was used to predict the emotion class probabilities.

Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 46, 46, 64)	640
conv2d_7 (Conv2D)	(None, 44, 44, 64)	36928
max_pooling2d_3 (MaxPooling2D)	(None, 22, 22, 64)	0
dropout_4 (Dropout)	(None, 22, 22, 64)	0
conv2d_8 (Conv2D)	(None, 20, 20, 64)	36928
conv2d_9 (Conv2D)	(None, 18, 18, 64)	36928
max_pooling2d_4 (MaxPooling2D)	(None, 9, 9, 64)	0
dropout_5 (Dropout)	(None, 9, 9, 64)	0
conv2d_10 (Conv2D)	(None, 7, 7, 128)	73856
conv2d_11 (Conv2D)	(None, 5, 5, 128)	147584
max_pooling2d_5 (MaxPooling2D)	(None, 2, 2, 128)	0
flatten_1 (Flatten)	(None, 512)	0
dense_2 (Dense)	(None, 1024)	525312
dropout_6 (Dropout)	(None, 1024)	0
dense_3 (Dense)	(None, 1024)	1049600
dropout_7 (Dropout)	(None, 1024)	0
dense_4 (Dense)	(None, 7)	7175
=====		
Total params: 1914951 (7.30 MB)		
Trainable params: 1914951 (7.30 MB)		
Non-trainable params: 0 (0.00 Byte)		

Fig. 1. DCNN Architecture Used for Facial Emotion Recognition

5) *Model Compilation and Training:* We used the Adam optimizer, accuracy as the evaluation metric, and categorical cross-entropy as the loss function for compiling the model. The preprocessed training data was used to train the model for a predetermined amount of epochs, and the testing data was used for validation.

6) *Model Saving:* After training, the model was saved to two separate files: 'fer.json' to store the model architecture and 'fer.h5' to store the model weights for future use.

C. Integration with ChatGPT:

The computed emotion label from the facial expression recognition model will be integrated into the user interface during the anticipated ChatGPT integration phase. The user's input will be accompanied by an emotion label in the terminal,

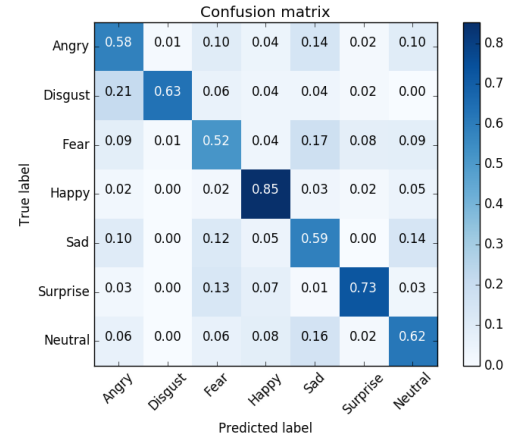


Fig. 2. Confusion Matrix for Emotion Detection from the Facial Images

producing a holistic prompt that combines textual context and emotional signals, even if direct integration with the ChatGPT API is still pending. This enhanced prompt will be effortlessly sent into ChatGPT upon successful API integration, allowing it to produce sympathetic and context-aware responses based on the user's emotional state. This method adds emotional intelligence to AI-driven discussions, resulting in a more responsive and personalised user experience. The testing process ensures the application's objective is met, evaluating accuracy based on facial expression images captured through the mobile phone camera. A total of 3589 images were used for testing. Fig 2 outlines the confusion matrix, indicating instances where the application wrongly recognizes emotions.

IV. RESULTS

We report the results of our model evaluation in this section using key metrics and visualisations. The examination includes crucial factors such as emotion recognition accuracy, the confusion matrix, and metrics such as precision, recall, and F1 score similar to evaluations done in [17] and [18].

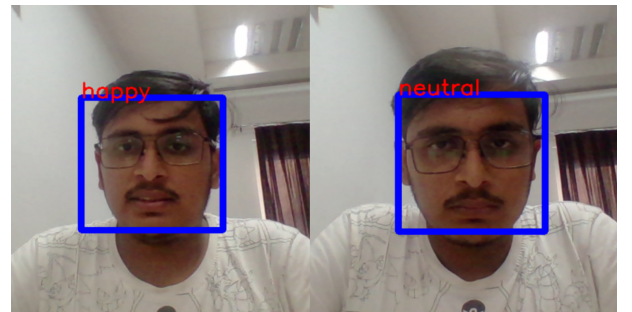


Fig. 3. Examples of Emotion Detection from the Facial Images

A. Accuracy and Loss Plots

The accuracy and loss charts are crucial for understanding the performance dynamics of our emotion recognition algorithm. These charts demonstrate how accuracy and loss

change during the training process. Accuracy is the fraction of accurately anticipated emotions, whereas loss is the difference between expected and real emotions.

These charts provide useful information about the model's learning trajectory. A rising accuracy curve indicates improved performance, showing that the model is collecting patterns in the data successfully. A falling loss curve, on the other hand, illustrates the model's capacity to minimise mistakes. Analysing these patterns contributes to a better understanding of the model's convergence, possible overfitting, and underfitting. The loss plot depicts the model's convergence by showing how

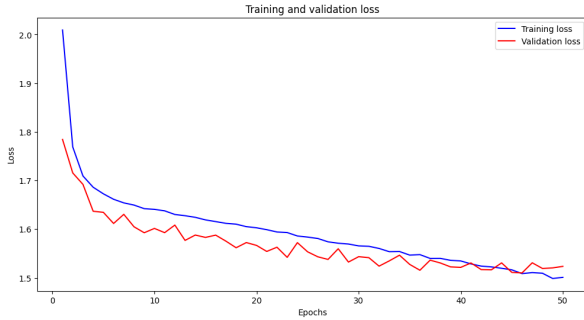


Fig. 4. Plot of Training and Validation Loss V/S Epochs

well it minimises mistakes. A decreasing loss plot indicates that learning has been effective, but oscillations or stagnation may suggest that training has been unsatisfactory.

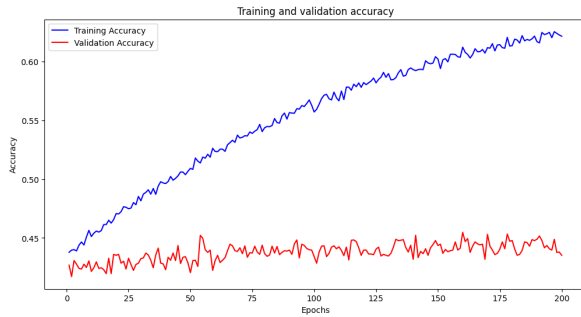


Fig. 5. Plot of Training and Validation Accuracy V/S Epochs

B. Evaluation Metrics

1) *Precision*: Precision is the ratio of correctly predicted positive observations to the total predicted positives.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

The precision for this application is 0.8576.

2) *Recall*: Recall is the ratio of correctly predicted positive observations to the total actual positives.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Recall for this application is 0.8526.

3) *F1-Score*: The F1 Score is the weighted average of precision and recall.

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The F1 Score for this application is 0.8525.

C. Summary of Metrics

Precision: 0.8576				
Recall: 0.8526				
F1 Score: 0.8525				
Classification Report:				
	precision	recall	f1-score	support
0	0.87	0.81	0.84	3995
1	0.89	0.95	0.92	436
2	0.93	0.75	0.83	4097
3	0.87	0.92	0.89	7215
4	0.85	0.81	0.83	4830
5	0.92	0.89	0.91	3171
6	0.75	0.88	0.81	4965
accuracy			0.85	28709
macro avg	0.87	0.86	0.86	28709
weighted avg	0.86	0.85	0.85	28709

Fig. 6. Summary of Evaluation metrics for the model

The following conclusions can be drawn from analysing the results of the evaluation metrics.

- The model demonstrates a balanced performance with good precision, recall, and F1 score.
- It is effective in correctly classifying emotions with a precision of 85.76%.
- The recall of 85.26% indicates the model's ability to identify the majority of actual positive cases.
- The F1 score reinforces the notion of a well-rounded model with a harmonious trade-off between precision and recall.

```

neo@neo-ubuntu: ~/Desktop/miniprojects/Sentiment-GPT
neo@neo-ubuntu:~/Desktop/miniprojects/Sentiment-GPT$ python3 videoTester.py
2023-11-03 16:46:20.388741: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:975] successful NUMA node
a read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node
zero
2023-11-03 16:46:20.421733: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load
dynamic library 'libcudnn.so.8'; dLError: libcudnn.so.8: cannot open shared object file: No such file or di
rectory: LD_LIBRARY_PATH: /opt/ros/noetic/lib
2023-11-03 16:46:20.421765: W tensorflow/core/common_runtime/gpu/gpu_device.cc:1850] Cannot dlopen some GPU
libraries. Please make sure the missing libraries mentioned above are installed properly if you would like
to use GPU. Follow the guide at https://www.tensorflow.org/install/gpu for how to download and setup the r
equired libraries for your platform.
Skipping registering GPU devices...
2023-11-03 16:46:20.422144: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is
optimized with oneAPI deep neural network library (oneDNN) to use the following CPU instructions in perform
ance-critical operations: AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
Press N to enter a new prompt :
Enter the prompt you want to ask ChatGPT : Can you suggest good music to listen to?
total emotions values [0.04773780175310094, 1.5493621321471807e-06, 35.02254478633404, 51.953638792037964,
0.6389968197327107, 0.1777713570627384, 40.1593892828989]
Your prompt is:
Your current emotional state is : happy
Your prompt is You are chatting with someone who is not very close to you but you recognise them. They are
looking for the answer to a specific question and are in a happy mood. They ask you, Can you suggest good m
usic to listen to? You being a good friend, acknowledge their mental state and provide an emotionally accu
rate and appropriate response to them. Generate a response in a conversational tone that acknowledges the p
erson's emotion, tries to identify the reason for it from analysing the question they are asking and says a
response that is emotionally appropriate( tries to make them feel better if sad or encourages them if they
are happy or clarifies something if they're confused or calms them down when they are angry). Remember, yo
u are the person responding.
Press N to enter a new prompt :

```

Fig. 7. Final Prompt Generation

When the above prompt is inserted into ChatGPT, we see quite a significant variation in the sentiment of the response. The response is tailored to the person's emotion and the emotionally appropriate response makes the conversation more human-like.

Original Emotion	Prompt Source	Prompt Response from ChatGPT	Sentiment Analysis
Happy	Sentiment-GPT	Hey there! I'm so glad to hear you're in a happy mood! Music can be such a fantastic way to enhance that positive vibe. What type of music are you in the mood for? Something upbeat and energetic, or maybe something more mellow and soothing? Let me know, and I'll be happy to recommend some tunes to keep that smile on your face!	97% Positive
Angry	Sentiment-GPT	Hey there! It sounds like you're having a tough time right now, and I'm here to help however I can. I get that music trends can be a cool distraction or even a way to vent. If you're feeling up for it, how about diving into some upbeat and energetic tunes? Music has this incredible power to shift our mood, you know? Let me know if you'd like some recommendations to shake off that anger.	63.8% Positive
Sad	Sentiment-GPT	Hey there! I can sense that you're not feeling your best right now. I'm here for you. Music has this amazing way of reaching into our emotions, doesn't it? If you're up for it, how about I recommend some uplifting and feel-good tunes to brighten your mood? Sometimes a good playlist can work wonders.	91.2% Positive
Neutral	Sentiment-GPT	Hey! I hope your day's been alright so far. I see you're curious about music trends – that's a great way to explore and maybe find something new that resonates with you. There's a lot happening in the music world right now! If you're up for it, I can share some current hits or emerging artists that might add a bit of spice to your playlist. Whether you're looking for a beat to lift your spirits or something to match your current vibe, I've got your back!	51% Positive
Any Emotion	ChatGPT	Certainly! I'd be happy to recommend some music across various genres. Could you please specify the type of music you're in the mood for or any particular artists, bands, or genres you already enjoy? That way, I can tailor my recommendations to your preferences.	24% Positive

Fig. 8. Response Variation and Sentiment Analysis

V. CONCLUSION

In conclusion, this study addresses the challenge of enhancing ChatGPT's conversational capabilities by enabling it to understand and respond to user emotions expressed through facial expressions. The primary focus is on improving the AI system's ability to adapt its responses based on detected user emotions.

Artificial intelligence has become a fundamental part of our everyday lives in the digital age, affecting how we engage with technology. However, the absence of emotional awareness in AI relationships remains a crucial gap. Affective computing, a subset of AI, strives to overcome this gap by allowing robots to understand and respond to human emotions. Sentiment analysis, a major component of emotional computing, has typically relied on textual data, yet human emotions are rich and diverse, sometimes represented through facial expressions.

This research explores the integration of real-time sentiment analysis based on facial expressions into conversational AI systems. We have developed a deep convolutional neural network (DCNN) architecture that can process and interpret facial cues, allowing AI models to adapt their responses to user emotions. By addressing three sub-problems, including facial expression recognition, integration of sentiment data, and sentiment-aware response generation, we have taken significant steps toward bridging the gap between human emotions and AI interactions.

The integration of real-time sentiment analysis in conversational AI represents a substantial advancement, with implications for various domains, including customer service, mental health support, and human-computer collaboration. The potential to create more empathetic and contextually aware conversational experiences is a transformative prospect.

In the envisioned integration phase with ChatGPT, the emotional label obtained from facial expression recognition will be incorporated into the user interface. This approach aims to provide a comprehensive prompt, combining textual context and emotional cues for ChatGPT. This integration will enable ChatGPT to generate contextually relevant and empathetic responses based on the user's emotional state, promising a more personalized and responsive user experience in AI-driven conversations.

Overall, this interdisciplinary research endeavor holds the promise of advancing the field of human-AI communication and user experience, ushering in a new era of emotionally intelligent AI interactions.

VI. DISCUSSION AND FUTURE WORK

The current study lays the foundation for further advancements in facial expression recognition (FER) models incorporated into facial recognition. Several avenues for future research and potential enhancements to the methodology are identified such as :

A. Expansion of Dataset

Future research might benefit from a more diversified and broad dataset. The model's capacity to generalise across varied populations may be improved by expanding the dataset to

include a greater range of demographic features, cultural backgrounds, and age groupings.

B. Fine-tuning Hyperparameters

An in-depth examination of hyperparameter adjustment can have a considerable influence on model performance. Modifications to learning rates, batch sizes, and dropout rates might possibly improve the model's accuracy and generalization.

C. Incorporation of Attention Mechanisms

Integrating attention processes into the model design might help it focus on important face characteristics, potentially improving identification accuracy. Attention processes are especially useful for catching small subtleties in emotions.

D. Multimodal Approaches

Combining facial expression data with additional modalities, such as speech or body language, can help to provide a more comprehensive understanding of human emotions. Multimodal ways to improving the resilience and accuracy of emotion identification systems might be investigated in future study.

Additionally, we see this idea revolutionizing the concept of Human-Computer Interactions. Some of the applications potentially include :

- **Emotionally Enhanced Human-Machine Interaction :** By customising replies to users' real-time emotional cues, the integration of face expression detection into Chat-GPT improves human-machine interaction. This encourages more empathetic and responsive exchanges, which increases user engagement and happiness.
- **Chatbots for Personalised Emotional Support :** Chat-GPT can provide personalised emotional support by augmenting feelings and adjusting replies depending on identified emotional states. This programme generates a virtual companion that responds to the emotional requirements of the user and provides sympathetic help.
- **Emotional Feedback in Virtual Learning Environments :** In educational contexts, face expression recognition in Chat-GPT adds emotional input to virtual learning environments. The chatbot assesses students' emotions and adapts replies to increase engagement and give personalised support, hence improving the overall learning experience.
- **Chat Support for Emotional Health and Wellness :** Chat-GPT, which has been enhanced with facial expression detection, is a tool for emotional health and wellbeing assistance. Users engage in emotionally aware chats, obtaining recommendations customised to their emotional states, broadening the functions of chatbots beyond information providing to emotional well-being assistance.
- **Sentiment-Aware Customer Service Chatbots :** By incorporating face expression detection into Chat-GPT, customer support chatbots can better understand and respond to consumer moods. This software delivers more nuanced and compassionate support, eventually enhancing client happiness and the entire service experience.

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