Emotion Recognition Through GPT-4 Computer Vision Analysis of Facial Expressions

Greyson Shafiei

University of North Carolina at Charlotte

May 5, 2025

Abstract

Recent advancements in multimodal large language models (LLMs) have demonstrated strong capabilities in processing and reasoning about visual information. However, their effectiveness in recognizing facial expressions remains underexplored, particularly in areas such as orientation and group contexts. This study aims to investigate the robustness of GPT-4's ability to classify facial expressions under various conditions. Using the WSEFEP set of standardized emotional facial expression stimuli, which builds on research from the Facial Action Coding System (Ekman & Friesen, 1978), GPT-4 was tested on images of facial expressions presented in upright and inverted orientations, as well as individual and matrixed contexts. The stimulus set included individual images that were manually compiled into facial matrices to analyze ensemble perception. It was hypothesized that GPT-4 would perform better in upright, individually presented faces and less accurately with inverted or matrixed presentations. The findings revealed that GPT-4's emotion recognition is significantly impaired by inverted face orientations and matrix configurations, with upright individual images resulting in the model's best performance. In addition, providing explanatory prompts did not lead to any notable effect on accuracy, indicating limited alignment with human elaborative processing models. Machine learning analysis utilizing Random Forest Classification verified a non-random structured pattern in GPT-4's responses. These results emphasize the model's sensitivity to visual layout and perceptual complexity, suggesting that GPT-4's facial emotion processing partially mimics human perceptual mechanisms, although there are notable limitations in configural and ensemble processing.

Keywords: large language models, emotion recognition, GPT-4

Emotion Recognition Through GPT-4 Computer Vision Analysis of Facial Expressions

In recent years, there has been an explosion of artificial intelligence systems referred to as Large Language Models (LLMs) which have an increasingly broad range of capabilities. One of the recent models OpenAI released was GPT-4, which introduced the ability to scan images and extract data from the contents of the photo submitted. Multimodal LLMs like GPT-4 have demonstrated impressive capabilities in computer vision, including object recognition, contextual reasoning, and visual data interpretation. According to a technical report completed by Achiam et al. (2024), when GPT-4 was fed 3 photos of an unusual charging cord and prompted, “What is funny about this image? Describe it panel by panel”, GPT-4 was able to decipher that the object in the first image as a VGA connector, an incorrect cable type, being plugged into an iPhone. In the second image, it was able to scan the manufacturer's package that initially contained the cable and read that the cable was labeled as a “Lighting Cable” adapter with a picture of a VGA connector on it. In the last photo, GPT-4 could then detect the object as a close-up of a VGA connector with a Lightning connector at the tip. GPT-4 then compiled the information from the three images together to detect the humorous element of the image due to using a large, outdated VGA connector in a modern smartphone that uses a smaller charging port. The example used in the technical report highlights GPT-4’s ability to use reasoning and abstract thinking to connect the data extracted from the different photos as recognizable objects with unusual details that were atypically connected, which could be perceived as humorous, properly satisfying all elements of the chat request.

Chat-GPT, like other LLMs, identifies and processes elements based on statistical patterns learned from massive data sets. GPT-4 must first process the image into patterned features using vision transformers, which are a form of neural network (Lahat et al., 2024). These transformers break the image down into patches and convert them into embeddings, which are numerical representations of the data. These embeddings are then processed by the transformer architecture, where the data is sent through hidden layers of the neural network, and the activation of the different nodes is compared along with the learned weights to create an output based on these influences (Lahat et al., 2024). The process thus uses pattern recognition and decision-making in deep learning algorithms to compare data in the hidden layers to the output layer, which is then used to create a final decision. It is important to note that these machines do not possess many of the cognitive abilities that humans have, but are statistical systems that can perform many of the same complex tasks that people can. LLMs do not have consciousness or subjective, emotional states. Thus, there is a need to better understand the gaps between human and LLM performance in visual cognitive abilities (Cao et al., 2024).

Classifying Emotional Facial Expressions

A landmark study of cognitive psychology was completed by Ekman & Friesen in 1978, where they established how humans express basic emotions through facial expressions and labeled their system the Facial Action Coding System. In this system, they established the facial movements that described six basic emotions. These six basic emotions were established to be cross-culturally experienced, which include anger, disgust, fear, happiness, sadness, and surprise. This is critical to the study at hand because it allows us to use a set of validated emotions for comparison, enabling higher accuracy since the emotions are cross-culturally experienced. This

means the dataset of photos is unlikely to be affected by emotions that are experienced by one culture but not defined by other cultures.

Another significant study showed that understanding facial expressions becomes difficult when faces are flipped upside down (McKelvie, 1995). Participants in that study became significantly less accurate when asked to identify the emotions of inverted faces than right-side-up faces. McKelvie argued that there are two kinds of processes that could support facial emotion recognition: Configural Processing and Componential Processing. Configurational processing refers to perceiving the overall layout and relationship between the different facial features. Componential processing is defined as the analysis of separate features, such as mouth shape or eyes, and how they are expressed (McKelvie, 1995). The study showed that people tend to rely on configurational processing when faces are in the standard, upright orientation, but rely on more componential processing when faces are inverted.

A vital machine learning study by Marian et al. (1999) measured facial expressions by using computational image analysis. The study resulted in an automated facial expression recognition algorithm that achieved a high success rate at recognizing basic emotions. The computer was trained to recognize facial feature shapes for a decision-based output. This is similar to the componential processing that McKelvie referred to in their work. The computer analysis, however, struggled with minor changes in facial expressions where the expression became more complex or subtle. The study showed the incredible ability of machine learning to process facial expressions while still showing that such systems did not reach human levels of performance, including robustness under varying conditions. Since the survey in 1999, machine learning techniques and processes have become more efficient and can complete more complex tasks.

GPT-4 and Facial Recognition Capabilities

LLMs like GPT-4 have demonstrated new multimodal abilities, including facial image processing, but they remain fundamentally different from current traditional biometric recognition systems. A study completed by DeAndres-Tame et al. (2024) evaluated GPT-4's capacity for face verification and soft biometrics estimation, such as age, gender, ethnicity, and explainability of results. These soft biometrics refer to physical or behavioral characteristics that, while not individually identifying on their own, can provide insights from categorical information for recognition tasks. Although this relates to biometrics, GPT-4 is incapable of performing direct biometric matching, unlike traditional detection systems. They found that while GPT-4 can analyze facial features, it does not function as a true facial recognition system. Instead, GPT-4 relies on descriptive inference rather than biometric matching. This means that the responses provided by GPT-4 are an attempt to find patterns it can detect in the face and infer what the person is experiencing without determining who the person actually is. This suggests that its performance on tasks like face inversion or matrixed faces may be influenced by contextual cues rather than by actual facial feature configurations.

Further technical testing by Iyer et al. (2024) explored the integration of real-time analysis using facial expressions into GPT-based conversational models, exemplifying that AI can use facial emotion recognition to adapt to the user by curating responses based on user emotions. This suggests that GPT-4 has the ability to process emotional cues from faces, but its capabilities are held back due to the limitation of a dedicated biometric framework. In this study, the system captured faces with a standard 30 frames per second webcam instead of an RGB-D or NIR biometric scanner. The choice of camera limited the performance by having lower camera quality, where there is lower spatial resolution and dynamic range, causing the obscured fine

facial muscle movements. There was also an additional reliability issue due to temporal fidelity with the low frame rate, which provided motion blur that prevented the reliable detection of micro-expression dynamics. In the context of the current study, it is key to determine if GPT-4's facial emotion recognition is affected by orientation and complexity or if the performance remains constant throughout under varying conditions.

Ensemble Representation in Facial Perception

Ensemble representation is a fundamental cognitive mechanism in human visual perception, allowing individuals to create a summary from a group of objects or faces instead of processing each of the several elements individually. Bayne & McClelland (2018) argue that ensemble properties, for instance, the mean of the emotion of a group of faces, are directly encoded in visual experience, which allows for rapid recognition of trends in large-scale visual stimuli. Research suggests that when humans view multiple faces simultaneously (e.g., when viewing a crowd or audience), they automatically form an impression of the average emotional expression rather than focusing on each individual face (Haberman et al., 2015). This ability is crucial for social perception and may have unique implications for machine vision models. At present, it is unknown whether multimodal LLMs process groups of facial expressions differently than humans, including whether they can efficiently extract the average expression of faces that are simultaneously present.

The present study examines whether GPT-4 exhibits similar ensemble perception abilities by testing the performance in recognizing emotions from a matrix of faces. If GPT-4 has difficulties with detecting group emotions but performs well on individual emotions, it could be an indication that its vision processing system lacks ensemble coding mechanisms. This is relevant when comparing its accuracy across individual upright faces, inverted faces, and

matrixed presentations, as ensemble perception theories predict that facial recognition should decline under conditions that interrupt typical configurational processing.

Present Study

GPT-4 demonstrates improved capabilities compared to the simplistic model used by Marian et al. (1999). The enormous database that GPT-4 was trained on provides the promise of being capable of processing facial expressions into emotions. The study by Marian et al. (1999) did not test the ability of the algorithm to process and accurately output emotions based on inverted facial expressions. Given the increased complexity of GPT-4 compared to the model of the previous study, there was no testing of the model's ability to average the mood of the faces shown, as well as the model's ability to decipher moods from a matrix of faces shown at one time. The current research expands on the prior findings by investigating whether GPT-4's multimodal vision capabilities align more with ensemble representation theories in human perception or if its performance is hindered by its reliance on text-based processing strategies.

The present study aims to test the ability of GPT-4 computer vision processing to interpret and translate facial expressions into emotions in different formats of visual data. In this study, GPT-4 was tested under different manipulated conditions: face orientation (upright vs. inverted), presentation style (individual vs. matrixed), and prompt style (with and without explanation). Classical statistical tests were leveraged to ascertain the accuracy of the model's predictions across the conditions, and then further explored using machine learning methods (Random Forest Regression) to determine if any specific patterns emerged from prompts led to predictive patterns in GPT-4's responses. These techniques revealed patterns in GPT-4's recognition behavior, suggesting that the outputs were structured and not likely to be random chance, but were influenced by the visual and contextual features. The findings reinforce the

notion that GPT-4's visual reasoning capabilities are sensitive to perceptual complexity and layout, aligning comparatively with ensemble theories while exposing limits in configural processing.

Hypothesis 1: GPT-4's ability to correctly identify facial expressions as emotions will not differ significantly from the human baseline accuracy of the dataset, at 82.35% (Olszanowski et al., 2015).

Hypothesis 2: GPT-4 will be able to categorize facial expressions into emotions at a similar success rate of inverted faces as normal-oriented faces.

Hypothesis 3: GPT-4 will have reduced accuracy in interpreting faces into emotions in a matrix format for both image orientations, compared to when presented as individual faces.

Hypothesis 4: GPT-4 will have a low success rate in identifying the average facial expression in face matrices, regardless of orientation.

In addition to the hypotheses above, I explored whether prompting GPT-4 to explain its classification decisions would lead to better performance. Other work with multimodal LLMs has shown that by providing LLMs with an example of correct work, it can improve the response outcomes. One approach to achieving these improvements is through asking the LLM to explain its reasoning, referred to as self-explanation prompting. Work by Gao and colleagues (2023) found that using this approach improved the response accuracy. They tested the models across six dialogue understanding datasets, which outperformed the zero-shot baselines (e.g., Chain-of-Thought and Plan-and-Solve), either matching or exceeding the performance of

few-shot prompting methods. Few-shot prompting refers to the process of providing the model with example questions and their corresponding answers (input-output pairing), and then asking the question for which a response is desired. The most substantial gains in performance were observed in the context of task-oriented dialogue, where a system is designed to assist a user in accomplishing a specific goal. An example of this would be a user using the system to make a reservation at a restaurant. In the study, it was found that when tested on the GPT-4 model, the self-explanation strategy yielded the best overall results. A key note of the study was that there was limited improvement when the task being performed related to emotion recognition. The authors suggest that it could be more suited for demanding context tracking rather than emotional recognition.

Methods

All code used to preprocess images, interact with GPT-4, and conduct the statistical and machine learning analyses is available on GitHub.

Materials

A sample of facial expression images was obtained from the *Warsaw Set of Emotional Facial Expression Pictures* (WSEFEP) developed by Olszanowski et al. (2015). This validated dataset includes 210 photographs from 30 individuals (14 men and 16 women), each portraying one of the six basic emotions: happiness, surprise, fear, sadness, anger, and disgust, as well as neutral expressions. The images were accessed through the Open Science Framework (Olszanowski et al., 2015), and the set is widely used in emotion research due to its controlled visual properties and diverse representation of affect.

The experiment used GPT-4, an LLM with computer vision capabilities for processing images, provided by OpenAI. GPT-4's multimodal functionality enabled it to visually analyze

the facial features and infer their emotional states using pre-trained knowledge and pattern recognition.

The complete set of individual facial expressions from the WSEFEP dataset was used to test GPT-4's ability to classify discrete emotional expressions. These images were presented in both upright and inverted orientations (Figure 1, top row). The six basic emotions used in this test align with those identified initially by Ekman and Friesen (1978) in the Facial Action Coding System. This setup provided a baseline for evaluating GPT-4's accuracy on single-image emotion recognition. They were then compared to the overall average agreement of the facial expressions recorded by Olszanowski et al. (2015), which served as the average human baseline accuracy.

To assess ensemble perception, selected individual faces from the dataset were manually composed into matrices consisting of 16 individual facial expressions displayed simultaneously. Each matrix was designed to include varied emotional compositions; however, each matrix was comprised of a single majority expression (e.g., 10 joyful faces with a mix of other expressions for the last 6 faces). The matrices were presented to GPT-4 in the upright and inverted orientations (Figure 1, bottom row).

Design

The study implemented a within-subjects experimental design that manipulated three factors: (a) whether stimuli involved individual or matrixed faces, (b) whether the orientation was upright or inverted, and (c) whether GPT-4 was prompted for an explanation. This resulted in a total of eight conditions that tested GPT-4's performance under different constraints of perception to evaluate the model's robustness in recognizing emotions. The use of the WSEFEP dataset ensured that the emotional expressions were standardized across all conditions.

Procedure

1. **Image Preprocessing**: All images were formatted for compatibility with GPT-4's vision input requirements. The photos were all JPG with no watermarks and under the 20 MB limit set by OpenAI.
2. **Input to GPT-4**: The processed images were submitted to GPT-4 via Python scripts using the OpenAI API. Each submission included a structured prompt that (a) listed the seven allowable response options: anger, disgust, fear, happiness (joy), sadness, surprise, and neutral, and (b) explicitly instructed GPT-4 to select one and only one of those options. The prompt for individual faces asked GPT-4 to identify the specific emotion the person in the picture is experiencing. For the matrix images, the prompt asked GPT-4 to identify the average emotion the group is experiencing. The text for the prompts in all conditions is provided in Table 1.
3. **Orientation Testing**: Each image was tested in both upright and inverted formats to assess the impact of facial rotation on GPT-4's classification accuracy.
4. **Explanation Testing**: Each image in both orientations and image type (individual vs. matrixed) was tested using two different prompts. One prompt asked GPT-4 to provide only the emotion, while the other asked it to give the emotion and an explanation of why it selected that emotion (see Table 1).

Results

To evaluate the multiple hypotheses, quantitative analyses were conducted to examine the accuracy rates of GPT-4 in classifying emotions from images of facial expressions across various orientations and configurations. The data were analyzed using Python and Scikit-learn to determine the association between these variables. Table 2 reports a complete descriptive overview of the emotion-identification accuracy of GPT-4 for all experimental conditions prior

to presenting statistical comparisons. Inferential statistics (t-tests and z-tests) were utilized to test the main hypotheses about differences in GPT-4's performance across the six conditions.

Hypothesis 1. On average, across all 912 images, the model correctly identified the emotion of the facial expressions in 59.5% (SD = 0.49) of the responses. A one-sample t-test comparing GPT-4's accuracy against the human benchmark of 82.35% showed a significant difference ($t = -14.026$, $p < .001$), indicating GPT-4 performed significantly worse than the human average overall.

Hypothesis 2. The accuracy was at 74% (SD = 0.44) when the faces were upright, but was at 45% (SD = 0.50) for inverted faces, replicating the inversion effect. A paired-samples t-test showed higher performance for upright faces (M = 0.74, 95% CI [0.69, 0.80]) than for inverted faces (M = 0.45, 95% CI [0.39, 0.51]), $t(227) = 9.96$, $p < .001$, confirming that inverted orientation significantly impairs GPT-4's recognition ability (Figure 2).

Hypothesis 3. In like manner, the emotion for individuated faces were identified correctly more often (M = 0.61, SD = 0.49) than the average emotion for matrixed faces (M = 0.41, SD = 0.50). An independent-samples t-test also revealed that individually presented faces (M = 0.61, 95 % CI [0.56, 0.67]) outperformed matrixed faces (M = 0.41, 95 % CI [0.20, 0.62]); however, this difference did not reach conventional significance, Welch $t(21.74) = 1.91$, $p = .07$, $d = 0.51$. This result did not support the hypothesis that matrixed presentations decrease accuracy, but this may be due to the small number of stimuli used in the matrix condition.

Hypothesis 4. A one-proportion z-test on matrixed face performance versus chance (14.3%) revealed that GPT-4 performed significantly above chance ($z = 4.899$, $p < .001$), showing ensemble perception capability to a degree.

Comparison of explanation vs. no-explanation prompts. Prompt style had a negligible influence: requests with and without commentaries (M = 0.59 and M = 0.60, respectively) produced overlapping accuracy estimates. A paired-sample t-test comparing prompts with explanations (M = 0.59, 95% CI [0.54, 0.64]) and without explanations (M = 0.60, 95% CI [0.55, 0.65]) showed no significant difference, t(227) = -0.96, p = .34.

Examination of accuracy by emotion. Figure 5, top row, magnifies this portrait even further by breaking down performance for each of the basic emotions and discovers that GPT-4 was strongest for joy, neutral, and surprise, and weakest for anger and disgust. This pattern did not vary whether by orientation or not. When comparing across conditions, Figure 6 reveals the model struggles to detect fear and sadness when presented in any condition other than individual upright images, but shows overall resilience to changes in any condition for the emotions of joy, neutral, and surprise. The corresponding confusion matrices (Figures 7–9) indicate where those errors occurred, for instance, reversed expressions of fear tended to be misclassified as surprise, and anger and disgust were often transposed with each other, illustrating systematic over random misperception.

Discussion

This study aimed to explore GPT-4's capability to accurately recognize emotional expressions across various visual conditions (upright vs. inverted and individual vs. matrixed) and prompt contexts (with explanation vs. without explanation). The results showed significant variation in GPT-4's performance depending on these factors. Hypothesis 4 was supported, while Hypotheses 1-3 were not.

A notable result of GPT-4's performance was that it performed significantly above chance (1/7 or 14.3%), but still fell below the human baseline accuracy reported by Olszanowski

et al. (2015) on the dataset. The model demonstrated greater accuracy with upright and individually presented faces, which resembles the human-like impairments in configural processing under the inversion observed by McKelvie et al (1995). Uniquely, the presence vs. absence of explanation prompts did not lead to a significant overall impact on GPT-4's accuracy of labeling the emotion, which does not reflect the human-like chain of thought discussed in the ELM. This raises questions about the internal reasoning techniques the model utilizes to exhibit a response.

The additional use of machine learning tools, such as Random Forest Classification, revealed that the model exhibited structured behavior in its responses. This supports the notion that consistent visual and context cues heavily influence GPT-4's visual decisions. A Random Forest Classifier trained on encoded features achieved an accuracy of 89% on a held-out test set (N = 274, Figure 10). Feature importance analysis indicated that variables such as orientation, face type, and emotion category were the strongest predictors of GPT-4's accuracy (Figure 12). These findings support the hypothesis that GPT-4's emotion recognition capabilities are modulated by cognitive-like processing conditions, paralleling human tendencies in interpreting facial expressions.

An additional exploratory comparison was used to determine if GPT-4 mimicked the human effect of elaboration on judgments, like that observed in the Elaboration Likelihood Model (ELM). There were two different prompts, one that asked GPT-4 to only choose the emotion displayed, and the other one asked the system to choose the emotion displayed and the reasoning behind its selection. As explained in the ELM, people process thoughts through different routes. The central route refers to deep, analytical thinking, which occurs when a person is asked to elaborate on their reasoning and reflect on it in detail. In contrast, the peripheral route

refers to shallow, surface-level thinking, where less deliberate decision-making occurs (Petty & Cacioppo, 1986). The no-explanation prompt was used to model the peripheral route of thought, while the explanation prompt was used to model the central route of thought. Since the results of Hypothesis 5 suggest that prompting the explanation had no significant effect on accuracy, it is likely that GPT-4 does not successfully mirror human cognition in the manner of thinking more deeply about the subject it is analyzing by asking it to explain its decision-making. This is also notable in the matrix condition, where the model appeared to be unable to separately analyze the different faces and reason about the relative proportion of a given facial expression.

Strengths and Limitations

One of the primary strengths of this study is its integration of psychology with advanced machine learning and artificial intelligence tools. The study follows from the well-studied Ekman's foundational work on emotions, which discusses how six basic human emotions are recognizable cross-culturally. The study also draws on McKelvie's inversion effect and modern ensemble perception theory, allowing for a multifaceted assessment of GPT-4's performance. The study's methodological design also ensured standardization and control over variables, particularly by using a validated image set (WSEFEP) and manipulating factors within a within-subjects framework.

However, despite the study's strength, several limitations must be considered. First, the analysis was restricted to static images, limiting its ability to be generalized to real-time facial expressions. Another noteworthy limitation is that although the dataset used was validated, the emotional expressions were posed rather than spontaneous, lacking the reflection of real-world complexity. A final consideration is that the explanation prompt may have been of an inadequate length to elicit a response from GPT-4, where the model used deeper reasoning to analyze the

image. The model's lack of significant performance change suggests that GPT-4 may exceedingly rely on visual token features, rather than eliciting a response through the use of language.

A final limitation to consider is that the study used a relatively small dataset for the matrixed faces. The study only contained 40 total matrix samples (upright and inverted); a larger sample would lead to higher validation of the results presented. The larger sample should contain varying facial expressions to ensure a wholesome evaluation of the model's accuracy.

Implications

These findings have considerable implications for the use of LLMs in affective computing. GPT-4 shows favorable potential as a tool for facial emotion analysis, with performance patterns resembling similar aspects of human visual processing, such as residing accuracy under inversion and matrix presentation—the model's ability to perform low-level ensemble-style emotion classification is significant in the realm of using the capabilities for real-world applications like adaptive learning platforms, therapeutic tools, or emotion-aware AI agents.

With that, the failure of using explanation prompts to improve performance indicates GPT-4's reasoning may not reflect conceptual elaboration. This limitation is fundamental when considering the application of the model in areas of visual reasoning where understanding the rationale is crucial. As suggested by Gao et al. (2023), self-explanation prompts may be more suitable for questions where deep context tracking is essential, such as math problems, where tracking each step and completing them in a specific manner is necessary to obtain the correct result.

Overall, GPT-4 may be better suited as an assistive tool in emotion recognition tasks when paired with dedicated biometric or feedback systems, which can provide higher accuracy in recognizing emotions and then utilize GPT-4 to offer a linguistic explanation for why the biometric system chose that emotion. Pairing these systems could counteract GPT-4's current limitations in configural processing and nuanced interpretation. OpenAI is continually improving its LLM models, which means a future model may be able to address the current weaknesses in these areas.

Future Research

While this study offers novel insights into GPT-4's capacity for facial emotion recognition, several avenues remain for further exploration of its capabilities. A significant step in the right direction would be to incorporate dynamic stimuli, such as providing the model with a video of a person changing their facial expressions throughout the video's duration. This would highlight the ability of GPT-4 to track emotional changes over time, which would resemble real-world scenarios. This would emphasize the model's utility in adaptive and interactive systems. Allowing us to assess the feasibility of using the model in areas where accuracy is essential, such as educational software, therapy bots, or customer service interfaces.

Additionally, as OpenAI releases newer models, future studies could reproduce this study using a newer model and compare the results to determine if GPT-4's areas of weakness have been improved. Investigating how OpenAI improves its model could provide a deeper understanding of how visual transformers are utilized in operations surrounding image reasoning.

Lastly, further research could more heavily manipulate the prompt structure to more explicitly induce a process where the model uses deeper reasoning skills while analyzing the

image. Future research could explore this by using varying levels of detail, emotional vocabulary, or task framing, allowing for a more rigorous determination of whether specific linguistic cues can lead to more accurate or human-like reasoning from the model. Improving the prompting for the model could enable optimal performance and refine how GPT-4 is utilized in practice.

Conclusion

The present study provides evidence that GPT-4 exhibits imperfect performance in recognizing facial emotions across different visual and contextual conditions. While the model surpassed the random chance level of accuracy and displayed human-like perceptual patterns, it could not match the human baseline for the dataset and showed limitations in making judgments under inverted conditions or in matrix format, which exemplified the model's struggles with increased complexity. The machine learning analysis confirmed that GPT-4's emotion recognition is systematically influenced by visual features, indicating that it is able to recognize certain emotions with higher levels of accuracy, suggesting that its behavior is guided by patterns rather than randomness. These findings underscore the potential of GPT-4 in psychological and technological applications; however, further evaluation of the model is necessary before deploying it in emotionally sensitive contexts.

References

Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F. L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., Avila, R., Babuschkin, I., Balaji, S., Balcom, V., Bao, H., Bavarian, M., Belgium, J., Belgum, I., ... Zoph, B. (2024). *GPT-4 technical report*. arXiv. https://arxiv.org/abs/2303.08774

Bartlett, M. S., Hager, J. C., Ekman, P., & Sejnowski, T. J. (1999). Measuring facial expressions by computer image analysis. *Psychophysiology, 36*(2), 253–263. https://doi.org/10.1017/S0048577299971763

Bayne, T., & McClelland, T. (2019). Ensemble representation and the contents of visual experience. *Philosophical Studies, 176*, 733–753. https://doi.org/10.1007/s11098-018-1225-0

Cao, X., Lai, B., Ye, W., Ma, Y., Heintz, J., Chen, J., ... & Rehg, J. M. (2024). What is the visual cognition gap between humans and multimodal llms?. *arXiv preprint arXiv:2406.10424*.

DeAndres-Tame, I., Tolosana, R., Vera-Rodriguez, R., Morales, A., Fierrez, J., & Ortega-Garcia, J. (2024). How good is ChatGPT at face biometrics? A first look into recognition, soft biometrics, and explainability. *IEEE Access, 12*, 22548–22558. https://doi.org/10.1109/ACCESS.2024.3369833

Ekman, P., & Friesen, W. V. (1978). *Facial action coding system*. Consulting Psychologists Press.

Gao, H., Lin, T. E., Li, H., Yang, M., Wu, Y., Ma, W., & Li, Y. (2023). Self-explanation prompting improves dialogue understanding in large language models. *arXiv preprint arXiv:2309.12940*.

Haberman, J., Brady, T. F., & Alvarez, G. A. (2015). Individual differences in ensemble perception reveal multiple, independent levels of ensemble representation. *Journal of Experimental Psychology: General, 144*(2), 432–446. https://doi.org/10.1037/xge0000053

Iyer, A. A., Vojjala, S., & Andrew, J. (2024). Augmenting sentiments into Chat-GPT using facial emotion recognition. In *2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS)* (Vol. 1, pp. 69–74). IEEE. https://doi.org/10.1109/ICACCS57996.2024.10314682

Lahat, A., Sharif, K., Zoabi, N., Shneor Patt, Y., Sharif, Y., Fisher, L., Shani, U., Arow, M., Levin, R., & Klang, E. (2024). Assessing generative pretrained transformers (GPT) in clinical decision-making: Comparative analysis of GPT-3.5 and GPT-4. *Journal of Medical Internet Research, 26*, e54571. https://doi.org/10.2196/54571

McKelvie, S. J. (1995). Emotional expression in upside-down faces: Evidence for configurational and componential processing. *British Journal of Social Psychology, 34*(3), 325–334. https://doi.org/10.1111/j.2044-8309.1995.tb01076.x

Olszanowski, M., Pochwatko, G., Kukliński, K., Ścibor-Rylski, M., Lewicki, P., & Ohme, R. (2015). Warsaw set of emotional facial expression pictures: A validation study of facial display photographs. *Frontiers in Psychology, 5*, 1516. https://doi.org/10.3389/fpsyg.2014.01516

Petty, R. E., & Cacioppo, J. T. (1986). *The elaboration likelihood model of persuasion* (pp. 1-24). Springer New York.

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Ichter, B., Xia, F., Chi, E. H., Le, Q. V., & Zhou, D. (2022). Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, *35*, 24824-24837.

Table 1

Prompts used in each condition

Face type	Prompt style	Prompt text
Individual	No explanation	"What emotion is the person in the image experiencing (anger, surprise, disgust, joy, neutral, fear, or sadness)? Answer by choosing one of the options only. Format: answer choice. For example: sadness"
Individual	Explanation	"What emotion is the person in the image experiencing (anger, surprise, disgust, joy, neutral, fear, or sadness)? Answer by choosing one of the options, explanation of why you selected it. Format: answer choice, explanation. For example: sadness, The person appears to …"
Matrixed	No explanation	"What is the average emotion the group is experiencing (anger, surprise, disgust, joy, neutral, fear, or sadness)? Answer by choosing one of the options only. Format: answer choice. For example: sadness"

Matrixed	Explanation	“What is the average emotion the group is experiencing (anger, surprise, disgust, joy, neutral, fear, or sadness)? Answer by choosing one of the options, explanation of why you selected it. Format: answer choice, explanation. For example: sadness, The people appear to …”

Table 2

Descriptive Statistics by Condition

Face type	Orientation	Prompt style	N	Accuracy Mean	Accuracy SD
Individual	Upright	No explanation	208	0.769	0.422
Individual	Upright	Explanation	208	0.764	0.425
Individual	Inverted	No explanation	208	0.466	0.5
Individual	Inverted	Explanation	208	0.452	0.499
Matrixed	Upright	No explanation	20	0.5	0.513
Matrixed	Upright	Explanation	20	0.45	0.51
Matrixed	Inverted	No explanation	20	0.35	0.489
Matrixed	Inverted	Explanation	20	0.35	0.489

Figure 1

Example stimuli in each condition.

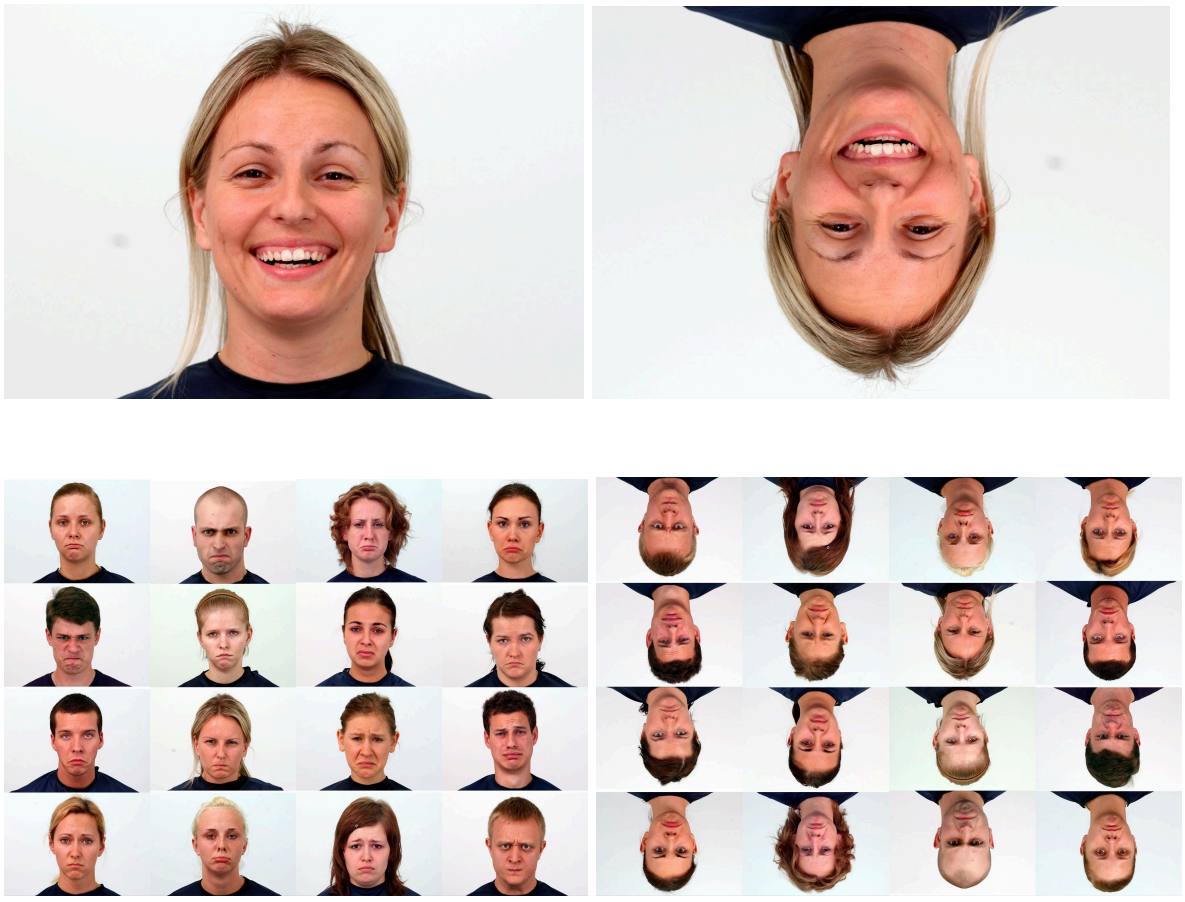
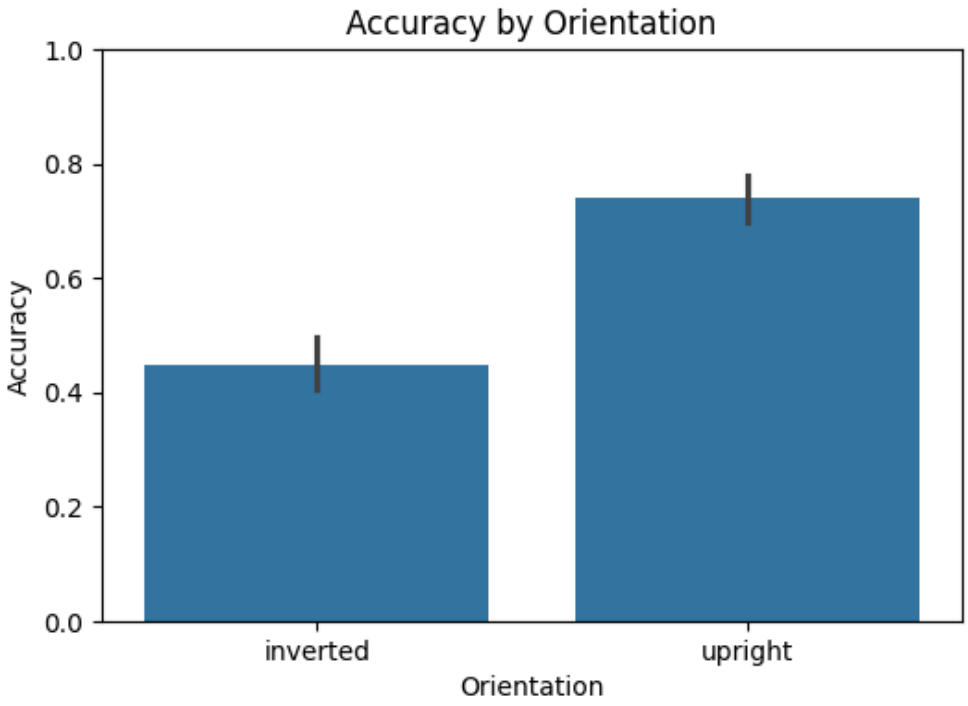


Figure 2

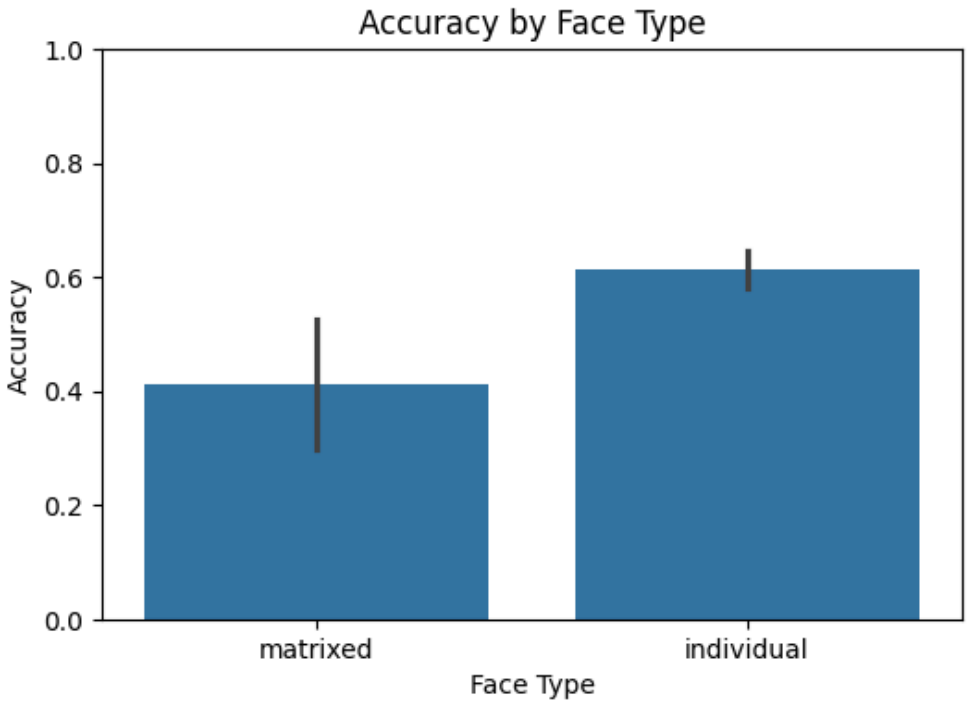
Bar chart depicting the overall accuracy rate between orientations.



Note. There is a significant drop-off in performance when the images are presented in inverted orientation.

Figure 3

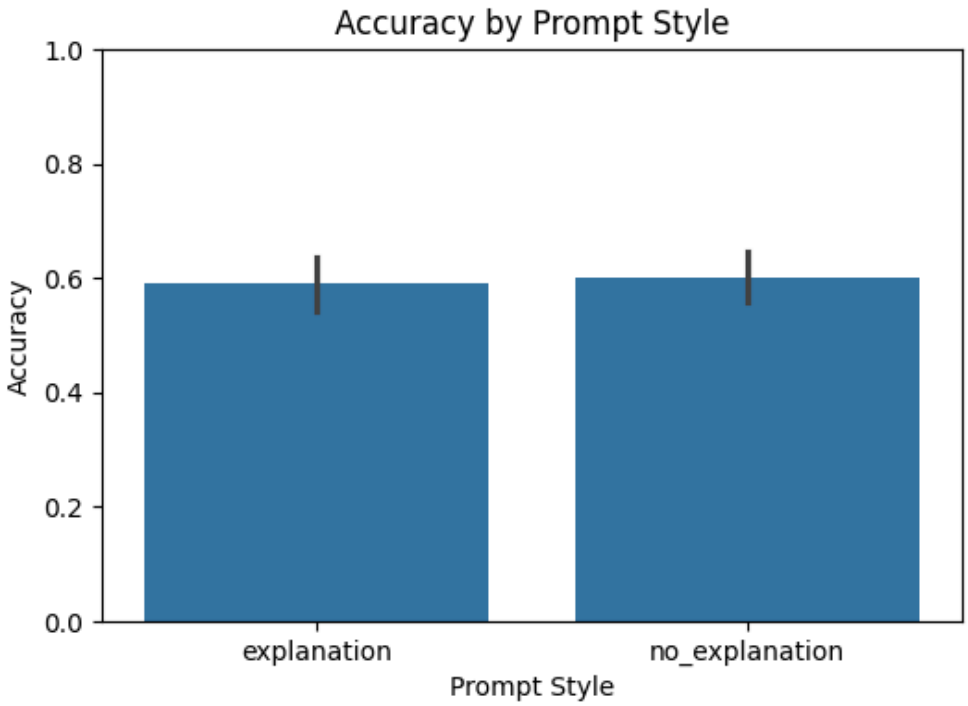
Bar chart depicting the overall accuracy rate between face types.



Note. The confidence band for the matrixed is much larger due to the small sample size of 40, while the individual sample size was 410.

Figure 4

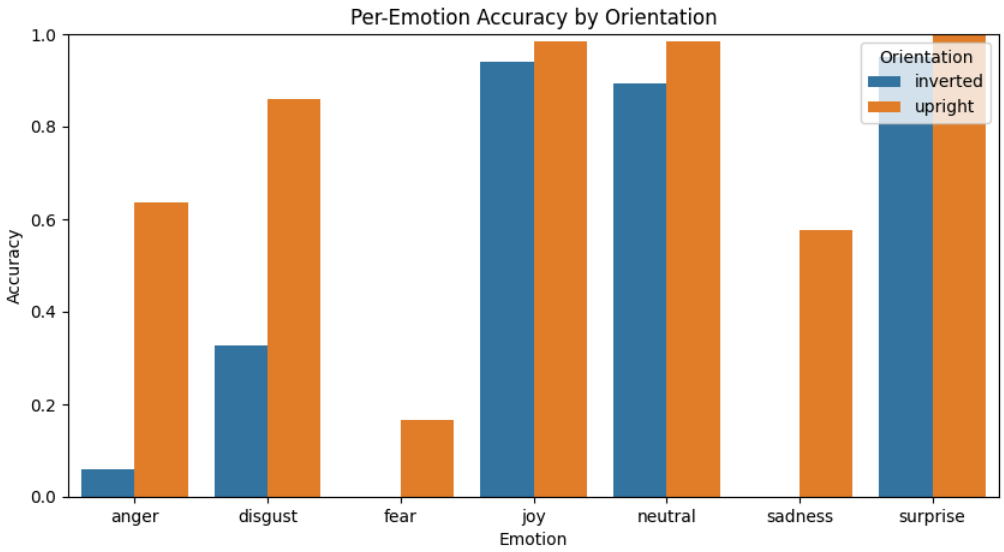
Bar chart depicting the accuracy rates between prompt styles.

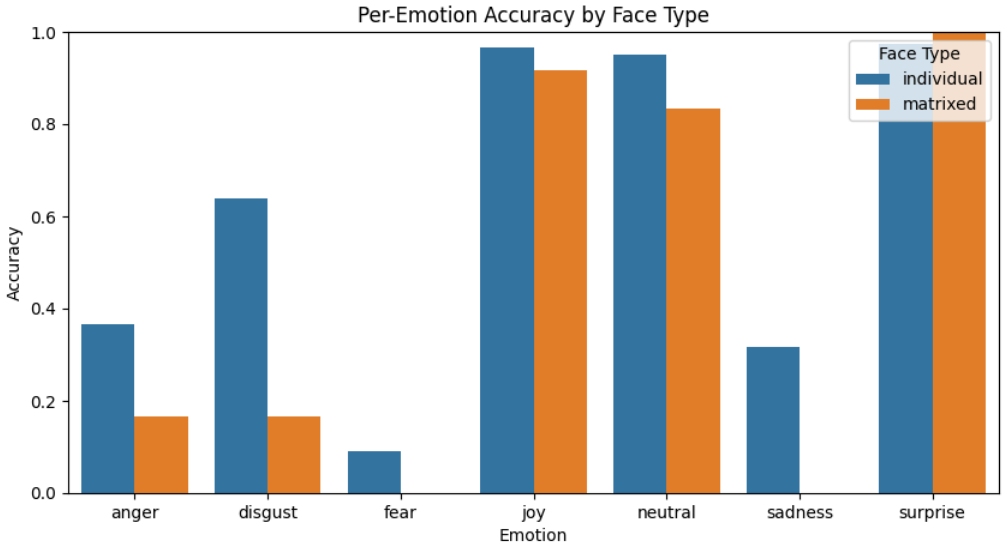


Note. The confidence range of the accuracy was nearly the same for both prompts.

Figure 5

Bar charts depicting the difference in accuracy rates between conditions across expressions.

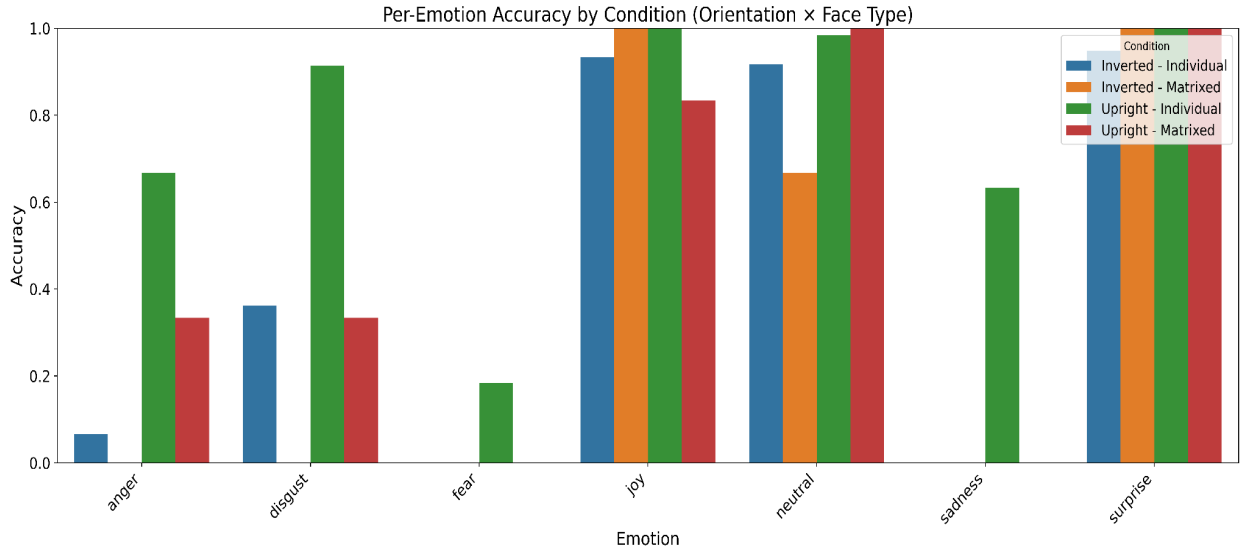




Note. Overall, the performance across all emotions was better when the images were upright or individual; however, there was a significant difference in accuracy when the presented emotion was ‘anger’ or ‘disgust’.

Figure 6

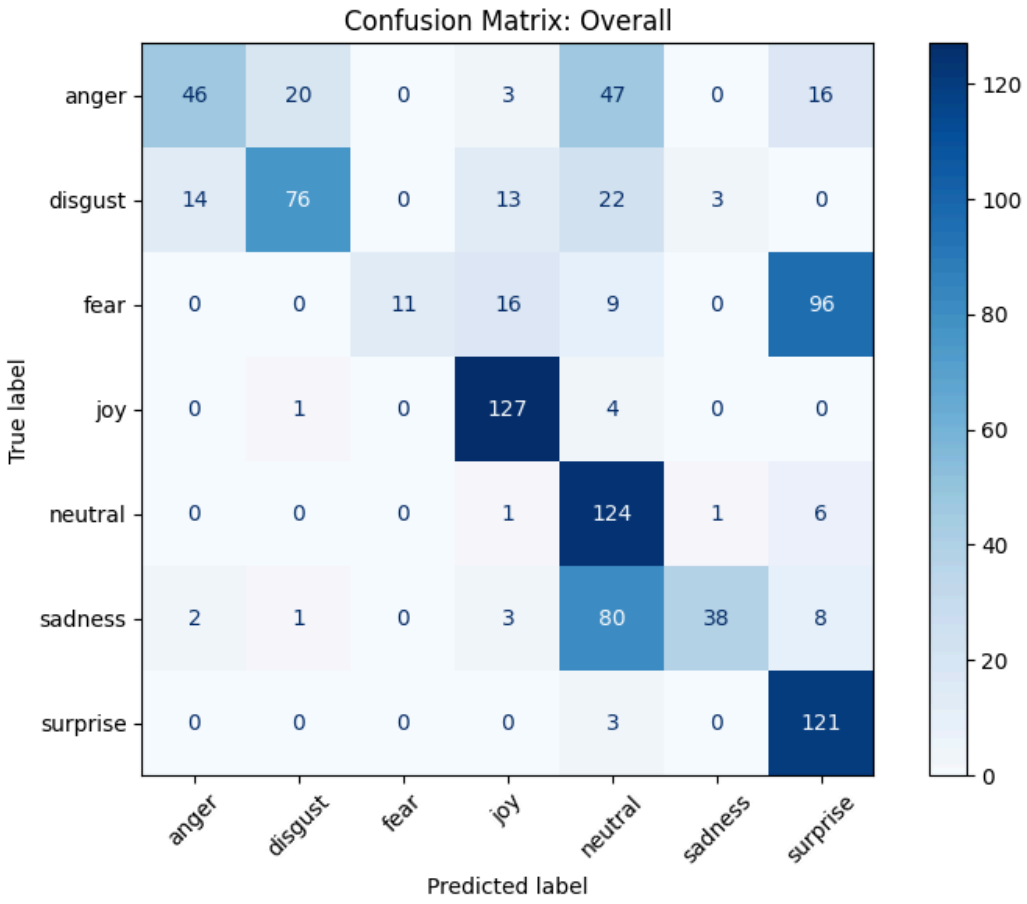
Combined Bar chart depicting the difference in accuracy rates between conditions across expressions.



Note. A higher resolution image can be obtained on GitHub. The figure shows that for emotions such as sadness and fear, the only success in detecting the emotion was achieved in the individual and upright format.

Figure 7

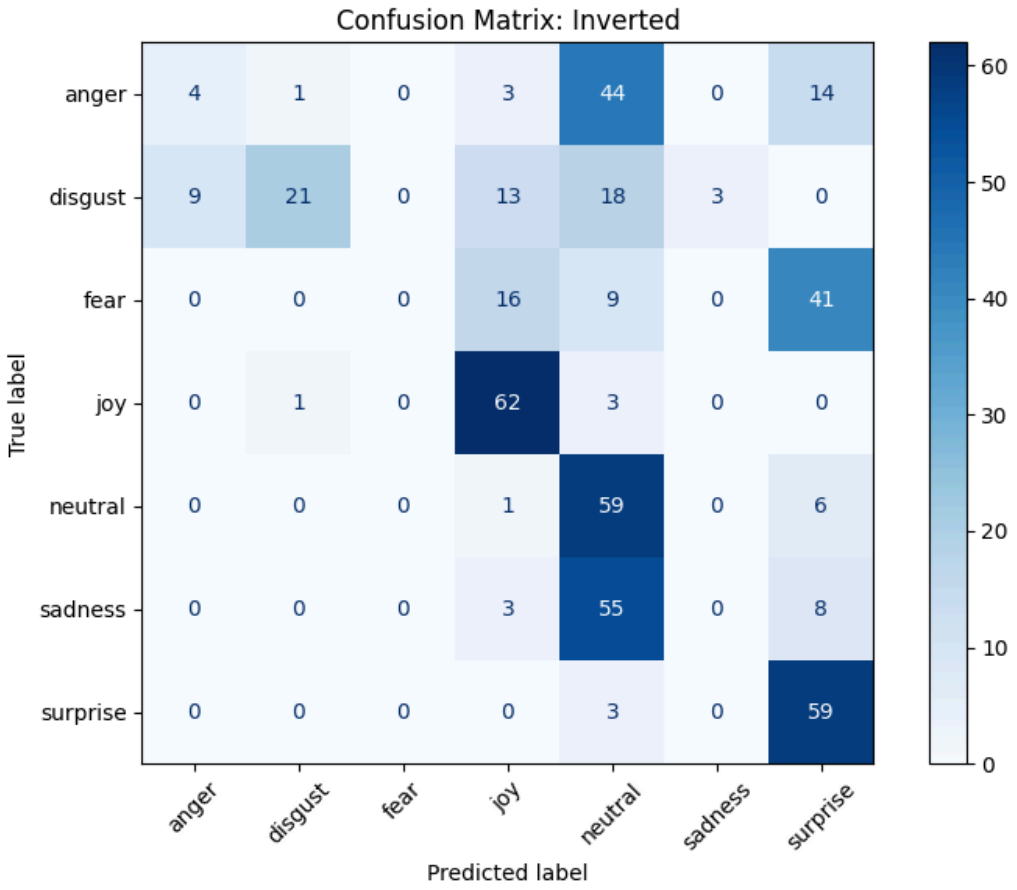
Confusion matrix of the overall responses, comparing them to the true facial expressions.



Note. Overall, the GPT-4 performed more accurately when the image's true label was 'joy', 'neutral', or 'surprise'.

Figure 8

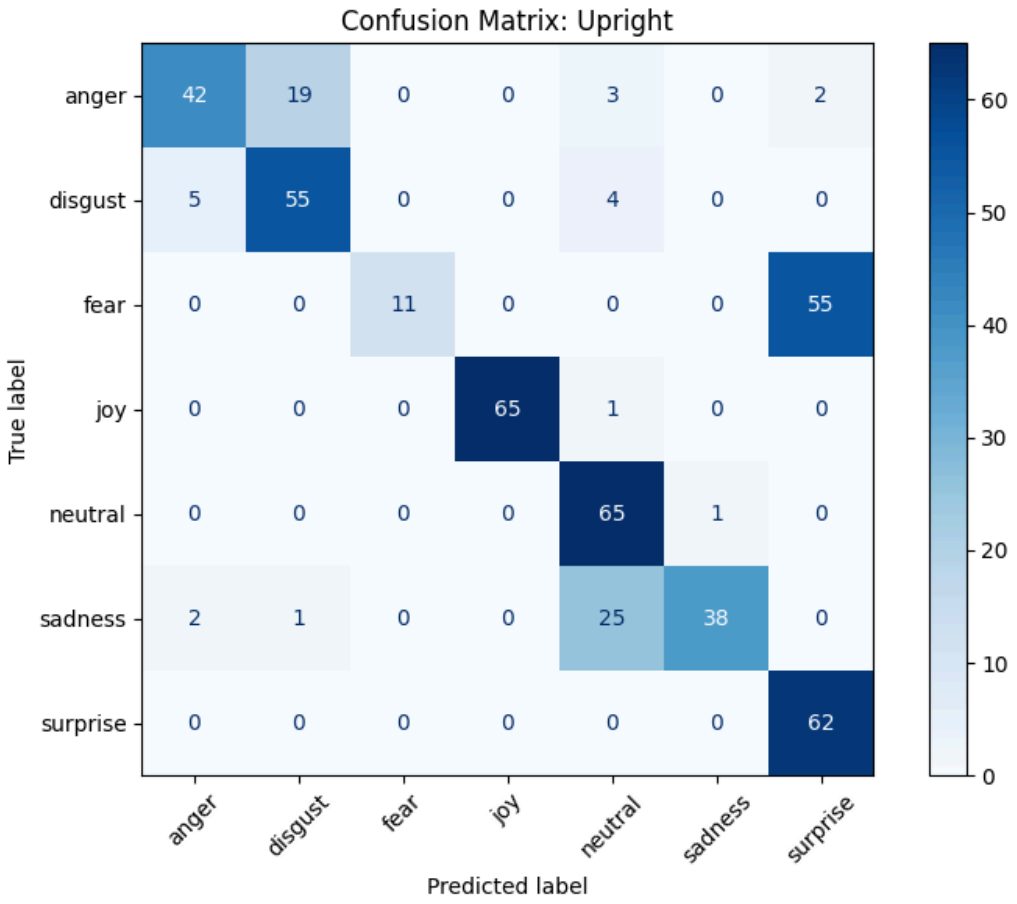
Confusion matrix of the inverted responses, comparing them to the true facial expressions.



Note. The inverted responses resulted in more sporadic predicted responses, leading to fewer matches with the true label.

Figure 9

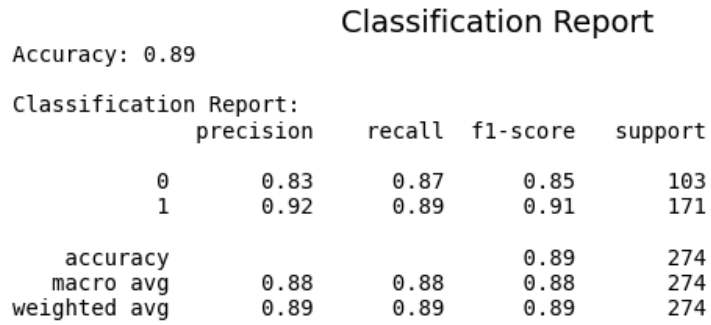
Confusion matrix of the upright responses, comparing them to the true facial expressions.



Note. The upright responses resulted in more predicted responses matching the true label.

Figure 10

The resulting accuracy of the Random Forest Classification model.



Note. The model produced an accuracy of 89%.

Figure 11

Confusion matrix of the Random Forest Classification model.

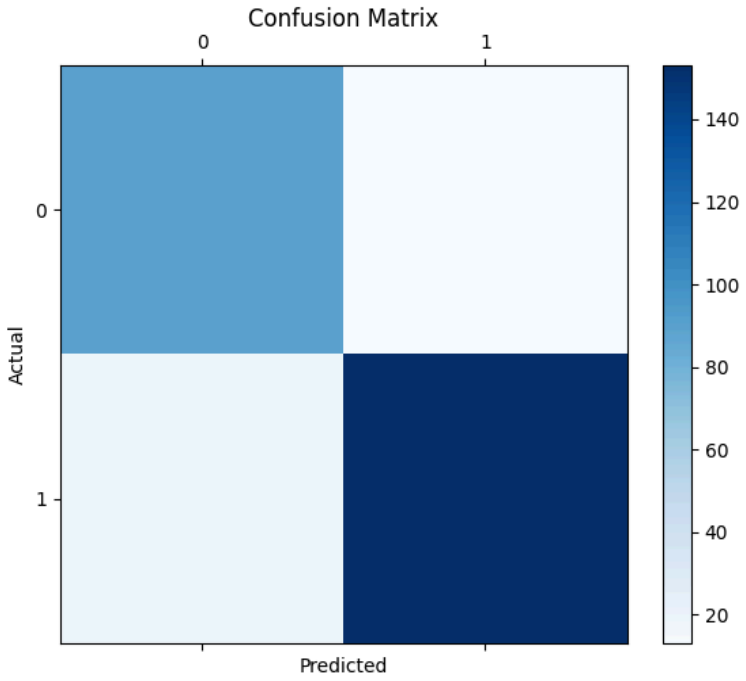
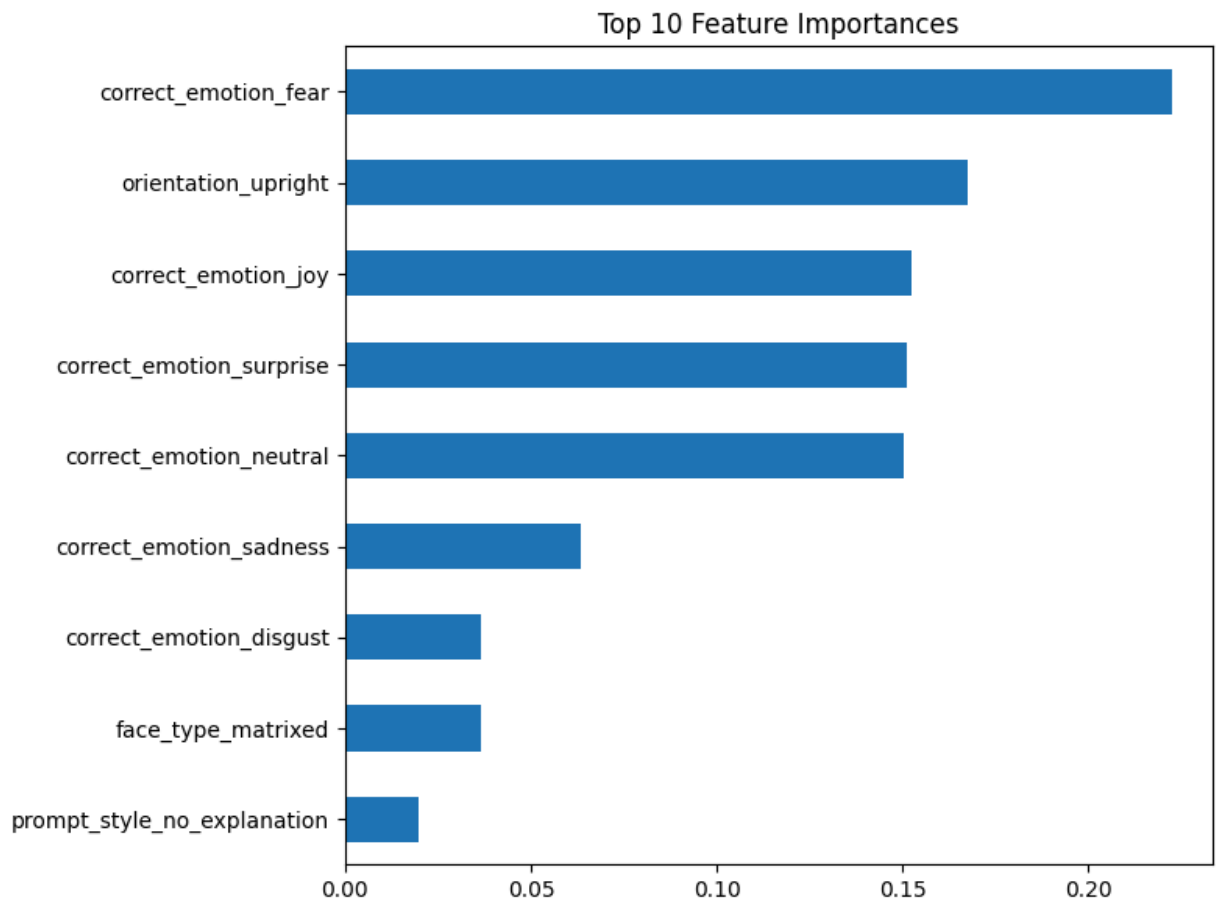


Figure 12

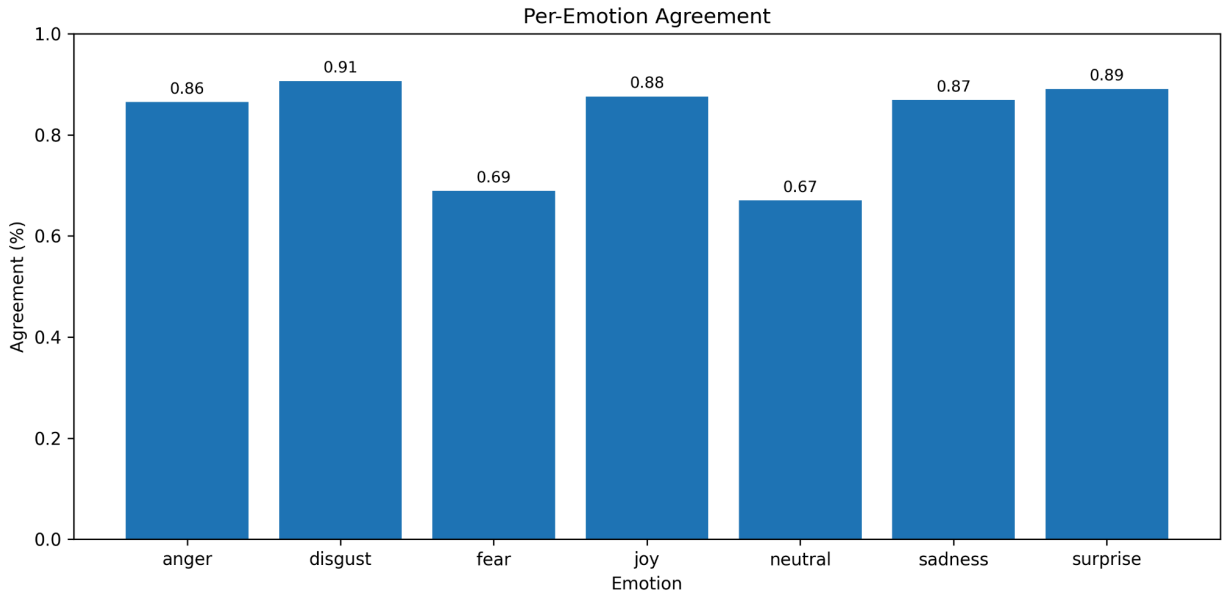
Top 10 Feature Importances in the Random Forest Classifier Predicting GPT-4's Emotion Recognition Accuracy.



Note. "Correct emotion: fear" and "orientation: upright" were the strongest predictors.

Figure 13

Mean human agreement for each emotional display in the WSEFEP dataset.



Note. The overall average agreement for emotion was 82.35%.