Emotion Detection with CLIP

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Abstract

Emotion detection plays a crucial role in various fields such as psychology, human-computer interaction, and market research [1, 2, 3]. Here, we present the creation of an AI model for detecting a specific emotion in human faces using deep learning. The model is trained on the FER2013 (Facial Expression Recognition 2013) dataset. Images from this dataset are fed into CLIP, an OpenAI model capable of turning both text and images into embeddings [9]. We then use these embeddings as training data for a multilayer perceptron (MLP) architecture to classify them into the target emotion category. The model achieves a classification accuracy of 71.40% on the test dataset, demonstrating its effectiveness in emotion detection tasks.

We then furthermore study the potential applications of CLIP by comparing the FER2013 image vectors to corresponding text vectors. As a result of these vector dimensions being too high for visualization, the dimensionality of the embeddings are reduced into 2 dimensions with the t-SNE technique for easy observation and comparison [5].

1. Introduction

1.1 Applications

The ability to accurately identify and understand the emotional states of individuals through facial expressions can lead to significant advancements in various domains [1, 2, 3]. Additionally, the analysis of the emotional content of human facial expressions is essential for the deeper understanding of human behavior [1]. Although natural for humans, the task of emotion recognition via computer systems proves to be a great task [4]. This further suggests the need for this research so we are better able to recognize and understand these human emotions through automation.

1.2 CLIP Experimentation

This research was also conducted to take a deeper dive into OpenAI's CLIP model and its capacity to generate image and text embeddings. These embeddings were invaluable to not only improve the performance of the emotion detection model simply trained on raw pixel data, but also to visualize these images in a different way, allowing spatial direction to correspond with meaning. The t-SNE technique proved to be invaluable for displaying the embeddings created by CLIP in a way that is easily understood, compared and measured.

1.3 Model Structure

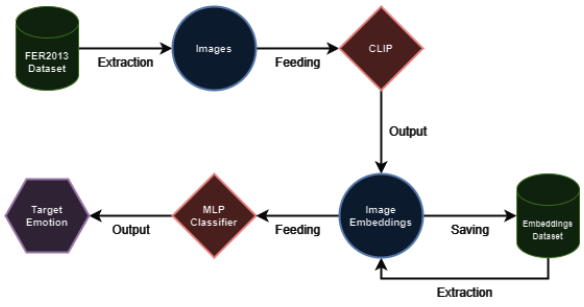

Figure 1: The training structure of the emotion model.

During training, the emotion detection model (shown in Figure 1) first takes the images from the FER2013 dataset and feeds them into OpenAI's CLIP model. CLIP converts these images into vectors (embeddings) which are then saved into a separate dataset. An emotion classifier is then trained on these image embeddings, which are each marked with their target emotion.

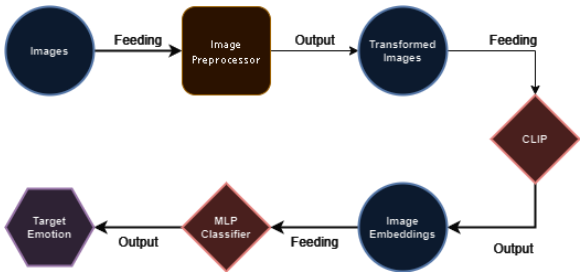

Figure 2: The application structure of the emotion model.

During application use, the model shown in Figure 2 takes inputted images and preprocesses them into a 48x48 grayscale image (the same image structure in the FER2013 dataset [6]). These preprocessed images are fed into CLIP which then translates the images into embeddings. The embeddings are then directly fed into the emotion classifier which will predict the emotion of the image.

2. Dataset

The FER2013 dataset consists of 48x48 pixel grayscale images of faces. The faces have been more or less centered and occupy about the same amount of space in each image [6]. The training set consists of 28,709 examples and the test set consists of 3,589 examples. Consequently, we train our model using the 28,709 example training set and test the model using both the training set and the 3,589 example testing set.

3. Experimentation

This section describes the development process for the emotion detection model as well as experimentation of the capacities of CLIP.

3.1 Emotion Detection Using Raw Images

It was first tested how a model would perform without the inclusion of CLIP within the model structure. An initial model was created that fed the raw images from the FER2013 dataset into an MLP classifier.

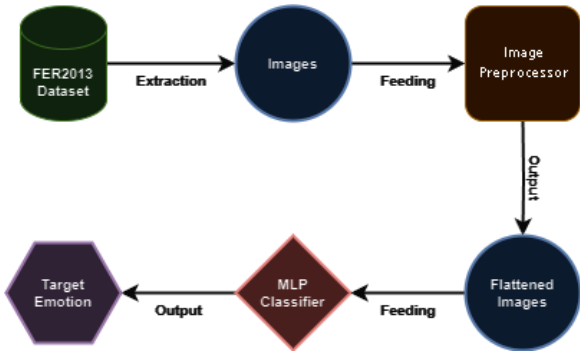

Figure 3: The training structure of the initial MLP emotion model.

However, the results of the model shown in Figure 3 were less than ideal. The best iteration of this model, after a rigorous fine-tuning of hyperparameters, had a testing accuracy of 41.40%, a result far lower than many other models trained on the FER2013 dataset who boasted an accuracy over 60% [7, 8].

To improve this performance, a different model was proposed utilizing a random forest classifier, opposed to the previously used MLP.

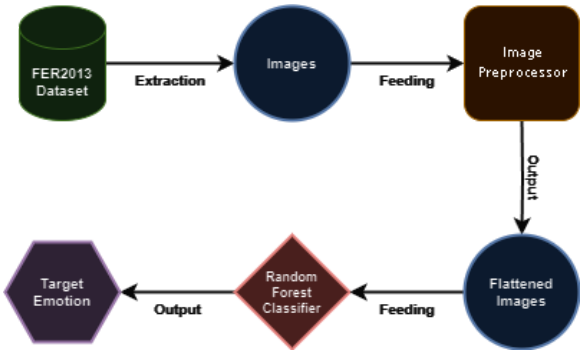

Figure 4: The training structure of the initial random forest emotion model.

The model shown in Figure 4, while outperforming the previously tested MLP model, was still underperforming. An ideal iteration of this random forest model with 10,000 decision trees presented a testing accuracy of only 48.90%, a result still far off from acceptable.

3.2 Emotion Detection With CLIP

OpenAI's CLIP model was effectively trained to convert image and text data into embeddings. We speculated these embeddings provided higher-quality training data to a classifier, resulting in a higher-performing model.

Since the random forest classifier outperformed the MLP classifier without CLIP, it was originally assumed that even with CLIP, a random forest will outperform an MLP.

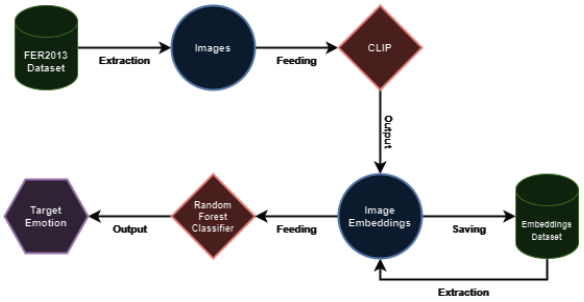

Figure 5: The training structure of the motion model using CLIP and a random forest classifier.

The addition of CLIP into the model structure (Figure 5) had a great effect on performance. This structure, using a random forest classifier with 10,000 decision trees, boasted an accuracy of 68.17%. This was a respectable accuracy, high among other emotion classification models trained on FER2013 [8].

Still, the model could be improved even more. It was still tested how an MLP classifier would perform when trained on the CLIP-generated image embeddings. As seen in Figure 1, the FER2013 image dataset was fed into CLIP to generate a dataset of image embeddings, which were then used to test an MLP classifier over many different combinations of hyperparameters. By taking advantage of the many hyperparameters an MLP classifier provides, a model can be greatly fine-tuned to emotion detection. After rigorous experimentation, a model was trained resulting in the highest yet seen testing accuracy. The model returned with an accuracy of 71.40%, one of the best accuracies resulting from a model trained on the FER2013 dataset, outclassing many other well-researched and trained emotion classification models [7, 8].

3.3 Embedding Comparison With CLIP

The capacities of CLIP were further explored with a different kind of experimentation. We attempted to visualize both text and image embeddings created by the CLIP model.

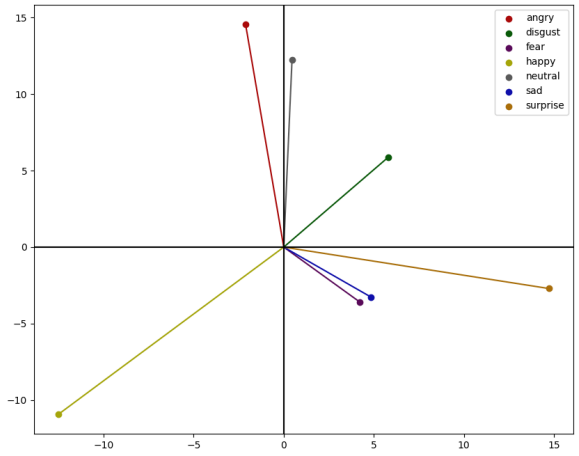

Figure 6: The image embeddings generated using CLIP and visualized through the t-SNE technique, averaged and categorized by target emotion.

The image embeddings displayed in Figure 6 present a conceptually interesting dilemma. Generally for humans, the opposite emotion of "happy" would be "sad" [10]. Interestingly enough however, the image embeddings depict the opposite of "happy" to be "disgusted" as evident through the two vectors being seemingly reflected on both the x- and y- axes. Looking back at the original point of data, the raw images themselves, this conclusion drawn from these embeddings seemed to be more or less supported. The FER2013 faces labeled as "disgusted" demonstrated the most negatively connotated and exaggerated facial features out of any other set of emotions. Oppositely, the faces labeled as "happy" had much simpler facial features with a much more positive connotation.

Furthermore, it was also found how similar the emotions "sad" and "fear" were, even when largely dimensionally reduced. This relation can be seen as self explanatory as humans often have similar facial expressions when feeling sad and fearful.

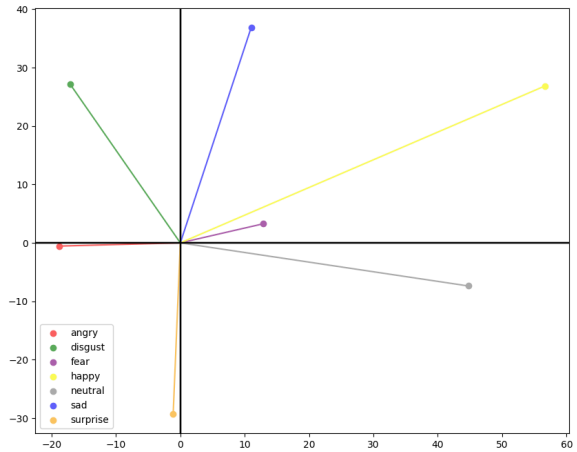

Figure 7: The text embeddings generated using CLIP and visualized through the t-SNE technique.

Text embeddings were created through forming sentences describing each human emotion. For example, the embedding for "happy" was created using the string "A happy human face". The text embeddings came to demonstrate none of the pattern found in that of the image embeddings. The vector for "happy" in Figure 7 demonstrated to have no x- and y-axes reflected opposite as it did in Figure 6. To further grasp the differences between the image and text dimensionally-reduced embeddings, an overlay including Figure 6 and Figure 7 was created.

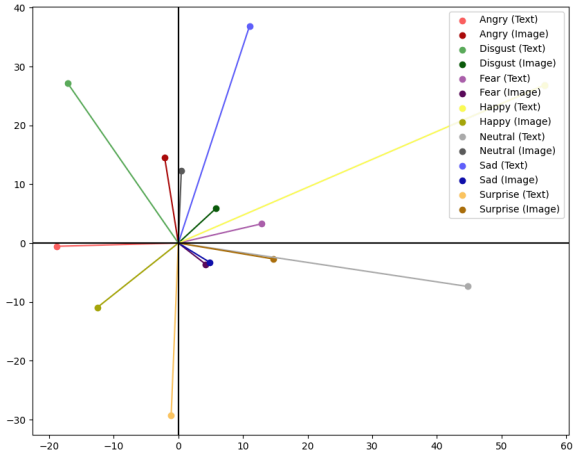

Figure 8: Figure 6 and Figure 7 overlayed onto the same graph for comparison.

An overlay between Figure 6 and Figure 7 were created to perhaps find a pattern between the image embeddings and their text counterparts. However, no such patterns were found as the image embedding visualizations were almost all unrelated to their text counterparts, evident by their near-perpendicular relationship between the t-SNE representations of the image and text embeddings for the majority of the emotions. This lack of relationship is likely reflected by the t-SNE technique which is in no way a perfect way to reduce the dimensionality of data for visualization as a large amount of data is lost with the dimensions.

4. Conclusion

When utilizing CLIP in tandem with an MLP classifier, a reliable model can be formed in which to accurately predict human emotion using images of faces. As mentioned, a model such as this has several applications [1, 2, 3]. Comparatively, CLIP - in cases such as that described within this paper - has the capacity to drastically improve the performance of models originally training on raw text or image data.

Furthermore, it was found that CLIP's capacity to generate embeddings have interesting relational capabilities such as the comparison of emotion expressed as both text and image embeddings.

References

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