Facial Expression Recognition

Final Project Report

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(All codes are available here: https://colab.research.google.com/drive/1YJZVdxNrWi6IgXHHHNndHOOnlh5p1-fh?usp=sharing)

Abstract

Computer vision is now able to analyze a lot of information, especially that related to facial detection. The human face has more than forty muscles that generate a wealth of expressions that can be communicated. For a human being, this understanding is innate and trying to make algorithms that reproduce it is a real challenge.

In this presentation, we presented our approach for sentiment analysis based on the use of pre-trained transformer models and networks using Pytorch. We used the AffectNet [1] database to train our models, starting with image preprocessing to improve their quality. We then used pre-trained models on ImageNet to extract features from the images. To predict the sentiments associated with the images, we used transformers, which showed good results in terms of accuracy. To understand how the models make their decision, we visualized the attention mechanisms to identify the most important areas in the images. Finally, we re-programmed a transformer from scratch and used input patches based on the important parts of the face to improve the prediction results.

For the project, we will create two libraries: Nexd and Lexd which respectively facilitate functions related to images, and functions related to landmark extraction. These are pip installable as can be seen in the colab at the top of this document.

1. Introduction

The project involves sentiment analysis based on the use of pre-trained transformer and network models using Pytorch. The aim of the project is to develop a system capable of recognizing facial expressions and associated sentiments using image analysis techniques.

The problem we aim to solve is to develop a system capable of recognizing facial expressions and associated sentiments, which requires a deep understanding of the underlying mechanisms of human facial expressions. This is a challenge due to the complexity of facial expressions, which are generated by over forty different muscles.

The questions we want to answer are: is it possible to develop a sentiment analysis system based on image analysis? If so, how can this be done effectively? How can models make predictions with high accuracy? How can the attention mechanisms of models be used to improve prediction results?

The problem is important because recognition of facial expressions and associated sentiments can have many applications in various domains. For example, autistic or blind people may need technology to read others' facial expressions, while the world of robotics may be very interested in a system capable of reading emotions for more intelligent interaction with users. Furthermore, in a more recent context where many people are wearing masks, facial expression recognition may prove difficult, making it an interesting challenge for algorithms.

Some potential applications include: real-time recognition of facial expressions for computer camera systems, helping people with illnesses to understand facial expressions, more intelligent interaction between robots and users by reading emotions, detecting dangerous situations by analyzing facial expressions of a crowd or driver, and recognizing facial expressions even when the face is partially obscured by a mask.

2. Problem Definition

In this work, we will first talk about landmarks. Facial landmarks (or facial keypoints) are distinct points on a face that allow for localization and measurement of specific features such as the eyes, nose, mouth, cheeks, etc. They are often used in face recognition and image processing algorithms to align and normalize face images, improve recognition accuracy, and facilitate the analysis of facial expressions. Landmarks can be determined automatically using detection algorithms or manually annotated. These points are defined by their real coordinates (x, y, z) on the image.

The feelings we are looking to study boil down to a subset of eight emotions that are labeled in the same database. In the AffectNet database, arousal represents the level of emotional excitement of a person. It can range from calm to highly excited. Valence, on the other hand, represents the emotional polarity, ranging from negative to positive. In other words, valence measures the degree of pleasure or suffering associated with a particular emotion. The arousal and valence annotations in AffectNet allow for the study of complex emotional expressions and for utilizing the information for applications such as sentiment analysis using images.

The pre-trained networks are deep learning models that have been trained on large amounts of data for a specific task. They can be used to improve the performance of models for new tasks by using the generalization capacity acquired during their initial training. Here, we will see the use of pre-trained networks for feature extraction to see the performance in our problem.

Transformers are a type of language processing model that uses attention to understand the structure of sentences and predict future tokens. So we will aim to use these different definitions for our sentiment classification for image analysis.

3. Related Work

- AffectNet: A Database for Facial Expression, Valence, and Arousal Computing in the Wild - This paper introduces the AffectNet database, which is a large collection of facial images annotated for facial expression, valence, and arousal. The authors aim to provide a comprehensive resource for the research community working on facial expression analysis and affect recognition.

- Reliable Crowdsourcing and Deep Locality-Preserving Learning for Expression Recognition in the Wild - This paper presents a method for expression recognition using deep learning and crowdsourced data. The authors use deep locality-preserving learning to leverage the crowdsourced data and achieve accurate expression recognition in the wild.

- Emotion Detection and Sentiment Analysis of Images - This paper focuses on the task of emotion detection and sentiment analysis from images. The authors propose a model that combines traditional computer vision techniques with deep learning to detect emotions and sentiment in images.

- Emotion Recognition across Cultures: The Influence of Ethnicity on Empathic Accuracy and Physiological Linkage - This paper examines the influence of ethnicity on emotion recognition accuracy and physiological linkage. The authors perform experiments to show that ethnicity can have a significant impact on the accuracy of emotion recognition and the physiological linkage between emotions and physiological responses.

- Understand and Implement Vision Transformer with TensorFlow 2.0 - This paper provides a tutorial on the Vision Transformer architecture, a type of transformer architecture designed for computer vision tasks. The author walks through the implementation of a Vision Transformer using TensorFlow 2.0.

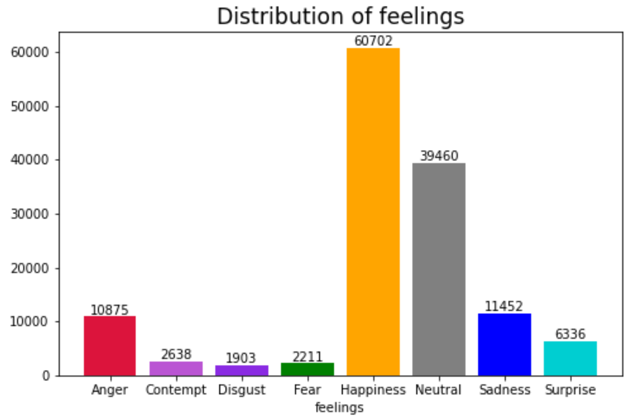
- Facial Expression Recognition with Inconsistently Annotated Datasets - This paper addresses the challenge of facial expression recognition when faced with inconsistent annotated datasets. The authors propose a method for facial expression recognition that can handle inconsistent annotations and still achieve good performance.

- Understanding and Mitigating Annotation Bias in Facial Expression Recognition - This paper focuses on the issue of annotation bias in facial expression recognition. The authors examine the sources of annotation bias in facial expression recognition and propose methods to mitigate this bias and improve the performance of facial expression recognition models.

4. Methodology

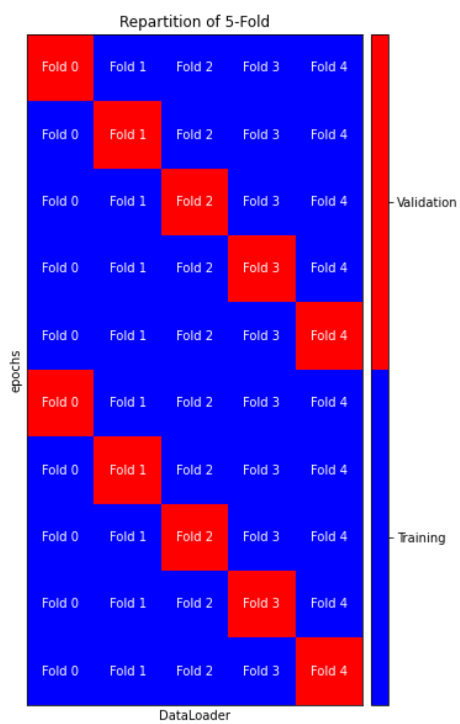
4.1 Data Preprocessing

The database is very poorly distributed. If we do not remedy this, we will be faced with a problem. Indeed, "Happy" faces represent 60% of the database. However, in the original paper, the overall accuracy is only 56%. Seeing this, we understand that the problem could be poorly handled and predict "Happy" faces to have a better success rate.



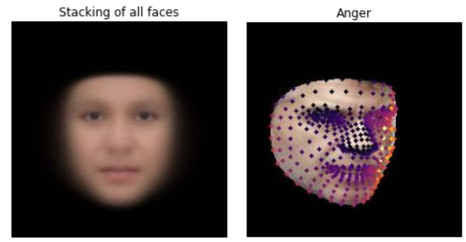
(Fig1: Distribution of feelings on AffectNet)

As we can see (Fig.1), the images are very poorly distributed and the number of occurrences for each class is completely different. For this work, the most common classes will be undersampled to form evenly sampled sets. We will then divide this work into k consecutive folds (Fig.2), keeping a percentage of the database to test our models with data that has never been seen before.



(Fig 2: for each epoch, the validation dataset is different)

The database is very large and does not only include human faces. To select the faces, we will use MediaPipe [2] here, which allows us to extract 468 3D landmarks if the face is human. The higher the detector coefficient, the greater the chance of having a human face. Since these points are always in the same position, we can extract the facial parts. This will allow us to have the position of the irises and the middle of the mouth, among other things. With these three points, we will be able to align all the faces so that the data has the least bias possible.



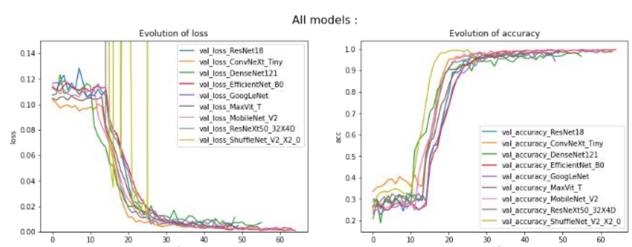
(Fig 3: (left) stacking of all the faces after our preprocessing, (right) 3D landmarks on a face)

With this treatment, the algorithms will all have the same type of images, we will reduce the biases that are related to positions or various variations.

4.2 Pretrained Models

The first part of the database analysis allows us to have a classic vision of understanding our database. We will use pre-trained models on Image-Net and specialize the classifier only at first. Then we will make the entire model trainable so that the other layers can also understand the emotions. The advantage of doing a cross-validation with k-folds is to reduce overfitting. As we can see on the training, the algorithms perfectly understand the sentiments but with the data set that no one has seen, the results are less good.

Indeed, the new data brings new faces, new biases that have never been seen and that is the problem. The Affect-Net paper boasts of having an accuracy of 56.4%, which we will find on the new data here. Data processing is therefore very important. Without treatment, there are 60% Happy faces so, by always putting this emotion we would have better results. This is not the goal.



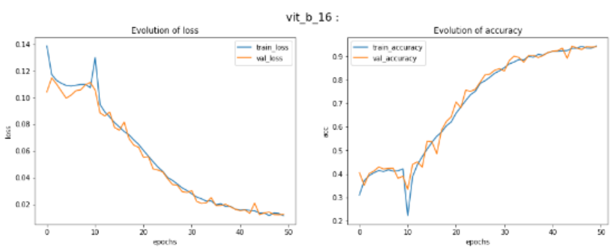
(Fig 4: Evolution of accuracy for each pretrained models)

To get better results, we will predict our data with all the models and average the results to reduce the error by weighting by the accuracy obtained during training. The goal is to reduce individual errors. For a case like ours, it is wise to weigh each sentiment by the score obtained for each model. Here, given that the final accuracy value is 100%, it is not very useful to weigh. This method gives us much more interesting results. Our success rate is the same as the paper but our variance is much lower! Each sentiment has the same percentage even when contempt is difficult to predict in the paper. We will see the results in the part 6.

5. New idea

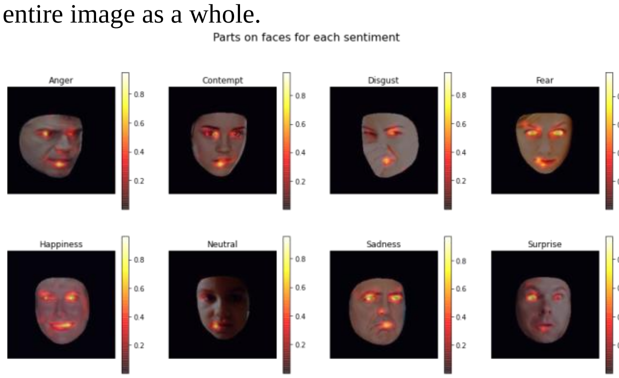
5.1 Attention Is All We Need

Transformer models have made significant advancements in a variety of areas, particularly in image analysis. The TransFER paper [3] demonstrates the use of a very simplistic dataset, but it shows that the attention mechanism can be visualized to better understand what our Transformers are learning. By visualizing the weights of our trained vit_b_16 model, as seen in previous models, we can gain insight into the areas of the image that the model focuses on.



(Fig 5: evolution of pretrained-vit_b_16)

As we can imagine, the model tends to focus on the expression that is located around the eyes and around the mouth. This is due to the fact that these areas of the face are known to convey the most emotion. Unlike other models, Transformers use an attention mechanism that is based on creating patches in the image [4]. This allows the model to focus on specific areas of the image, rather than treating the entire image as a whole.



(Fig 6: visualization of our weights)

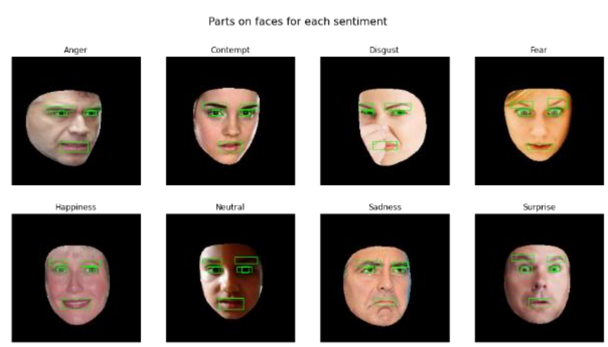
It is interesting to explore ways to select these patches and remove the least useful ones. This could potentially lead to improved performance by reducing the amount of noise in the data and allowing the model to focus on the most important areas of the image. Additionally, by understanding which areas of the image the model is focusing on, we can gain insight into the underlying mechanisms of the model and potentially improve its performance.

In conclusion, Transformer models have shown great promise in image analysis and have the potential to improve our understanding of the underlying mechanisms of image analysis. Through visualization of attention mechanisms and exploring ways to select and remove patches, we can gain insight into the model's decision making process and improve its performance.

5.2 Custom Transformer for Facial Expression

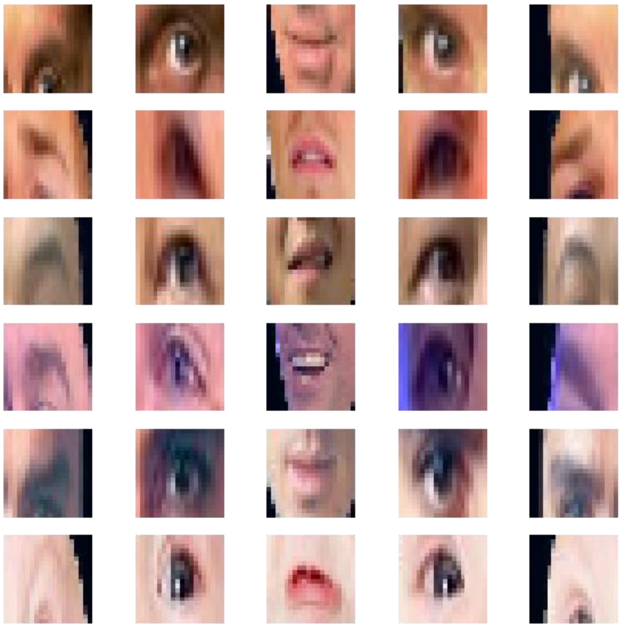
By extracting facial parts using landmarks, we can create our own patches. This allows us to target the most important areas of the image (Fig.6), thus reducing noise and improving performance. Additionally, by understanding the parts of the image the model focuses on, we can further improve performance by optimizing architecture parameters. Facial parts can be extracted using Mediapipe landmarks which are always indexed the same way. A visualization of these can be seen above (Fig.3).

To create an architecture that works perfectly, we had to recreate the Transformers and all the layers from scratch. This ensured that the model was tailored to our specific needs and was not limited by pre-existing architecture. It is now easy with our code to input anything we want to replace simple batches. This allows us to experiment with different input types and see how they affect the model's performance.



(Fig 7: parts on faces detected with Landmarks)

As shown in the figure, the parts of the face we keep are the eyes, eyebrows and mouth, slightly enlarging the area to keep more context. This allows the model to have a better understanding of the facial expression and predict emotions more accurately.



(Fig 8: patches on the input of our Custom Transformer)

The results are not as good as those seen in the other sections. Indeed, the weights are not pre-trained here and do not know in advance which parts of the image are important. However, for an architecture that is much smaller than the other models, we have the first emotions that are predicted just as well. This shows that our approach is efficient and that with further optimization, we can achieve even better results. We will see them in the next section.

6 Results & Evaluation

Our work has very good results when trying to determine the expression in real situations. Indeed, often, the expression on a face is not often unique and it is well seen. An expression is a set of micro-expressions and, during our training, we only try to predict one expression among the eight that we had. We can see that this assumption is true particularly for the Top2 accuracy.

In the following two figures, the results of the original paper are displayed in the first row. The values in green are the highest in the column and the values in red are the lowest.

Model_name_Top1	Anger	Contempt	Disgust	Fear	Happiness	Neutral	Sadness	Surprise	mean	variance
original_paper	0.6	0.32	0.64	0.57	0.68	0.49	0.6	0.63	0.566	0.011
ResNet18	0.5	0.36	0.54	0.58	0.59	0.38	0.59	0.44	0.498	0.008
ConvNeXt_Tiny	0.53	0.6	0.49	0.34	0.63	0.41	0.36	0.63	0.499	0.012
DenseNet121	0.46	0.26	0.53	0.64	0.79	0.36	0.45	0.48	0.496	0.023
vit_b_16	0.39	0.42	0.38	0.38	0.77	0.46	0.45	0.44	0.461	0.014
EfficientNet_B0	0.34	0.45	0.52	0.51	0.59	0.43	0.54	0.56	0.493	0.006
GoogLeNet	0.49	0.31	0.48	0.45	0.62	0.26	0.7	0.44	0.469	0.018
MaxVit_T	0.48	0.43	0.48	0.57	0.64	0.51	0.55	0.33	0.499	0.008
MobileNet_V2	0.45	0.48	0.51	0.37	0.67	0.42	0.41	0.43	0.468	0.007
ResNeXt50_32X4D	0.46	0.66	0.54	0.45	0.35	0.34	0.53	0.47	0.475	0.01
ShuffleNet_V2_X2_0	0.48	0.45	0.54	0.5	0.49	0.36	0.38	0.38	0.448	0.004
my_vit	0.4	0.41	0.31	0.28	0.81	0.07	0.19	0.05	0.315	0.051
all_models	0.54	0.52	0.57	0.53	0.66	0.51	0.55	0.49	0.546	0.002

(Fig 9: Top1 Norm Down-sampling result)

Model_name_Top2	Anger	Contempt	Disgust	Fear	Happiness	Neutral	Sadness	Surprise	mean	variance
original_paper	0.78	0.7	0.81	0.82	0.85	0.7	0.78	0.83	0.784	0.003
ResNet18	0.71	0.43	0.68	0.75	0.76	0.51	0.69	0.63	0.645	0.012
ConvNeXt_Tiny	0.71	0.76	0.66	0.47	0.77	0.61	0.49	0.83	0.662	0.015
DenseNet121	0.57	0.55	0.63	0.78	0.86	0.62	0.56	0.65	0.653	0.011
vit_b_16	0.54	0.57	0.46	0.53	0.85	0.79	0.57	0.71	0.628	0.017
EfficientNet_B0	0.61	0.56	0.64	0.67	0.75	0.63	0.69	0.73	0.66	0.003
GoogLeNet	0.62	0.45	0.58	0.67	0.76	0.38	0.81	0.77	0.63	0.021
MaxVit_T	0.71	0.59	0.64	0.69	0.84	0.64	0.71	0.61	0.679	0.005
MobileNet_V2	0.61	0.74	0.67	0.59	0.87	0.53	0.56	0.57	0.643	0.011
ResNeXt50_32X4D	0.7	0.79	0.72	0.64	0.46	0.52	0.67	0.65	0.644	0.01
ShuffleNet_V2_X2_0	0.67	0.64	0.65	0.73	0.65	0.57	0.56	0.64	0.639	0.003
my_vit	0.58	0.83	0.57	0.36	0.87	0.2	0.35	0.2	0.495	0.06
all_models	0.8	0.81	0.69	0.79	0.81	0.74	0.74	0.75	0.766	0.002

(Fig 10: Top2 Norm Down-sampling result)

There are several interesting observations to make. Independently, all models are worse than the results reported in the paper. The most interesting result concerns the voting learning. By combining the predictions of all models, we get a result that has almost the same mean prediction as the paper but, our variance is much lower (especially for Top1 accuracy). This shows that when we gather our models, they predict the entire set of emotions better, where the paper will poorly understand certain emotions.

We notice that our Custom Transformer, with our Attention mechanism, is very bad as it gets the worst scores for each possible prediction. This shows that there is still work to do on it. There is potential as for example it gets the best scores for happy faces. So it still needs more training to generalize.

Below are the results that our Voting-Learning predicts.

(Fig 11: result on a surprised face)

(Fig 12: result on a sad face)

Our model is well focused on trying to predict a single emotion as we can see. The results are therefore very good and allow us to confirm the results of the paper, understand them and even improve them.

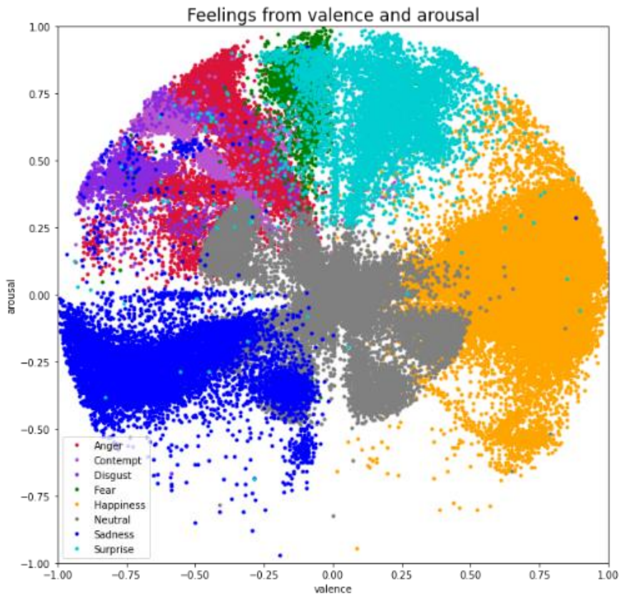
7 Conclusions & Ameliorations

Comme nous l'avons vu, nous avons testé plusieurs modèles qui ont des résultats différents. Notamment, notre modèle custom a des résultats plus faibles que nos modèles pré-entraîné. Néanmoins, le temps de calcul est bcp plus faible et il y a de la matière à améliorer.

To begin to solve this problem, it would be interesting to complicate the layers of our custom attention and adding, for example, a convolutional network that will extract on its own what our patches may not have captured. (This track has been started but not yet completed in terms of results).

The idea behind this approach is that we have a human vision that confirms what the Transformers visualize (Fig. 6) and we can easily extract these parts. However, for our model, perhaps other parts of the face that do not immediately come to mind are just as important. The idea of adding a convolutional network that learns at the same time as the Transformer is that it will create filters, that is, parts of the image for each filter. These can be added in parallel to our previous patches (Fig. 8). And, this network would learn on its own what it considers important in addition to the patches.

In a second part, the prediction of valence and arousal is to be paralleled with this work. Valence refers to how positive or negative an event is and Arousal reflects whether an event is exciting/agitating or calm/soothing. Indeed, the AffectNet database is also composed of this information which is not used at all in this work. Here, the project focused solely on image-based extraction. As we obtain the results of the paper with just the images, we can think that the addition of this will only be beneficial and we will easily exceed our performance.



(Fig 13: emotions from Valence and Arousal)

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