Emotions detection using Convolutional Neural Networks.

Abstract

The current document presents the implementation of CNN model to predict 3 types of emotions,anger ,happiness and astonishment.

Introduction

Emotions are crucial in marketing, they are a means in captivating and influencing consumers. The relationship between emotions and consumer behavior has been the subject of extensive research and has given rise to a diverse range of marketing strategies and techniques.When it comes to advertising and branding, evoking emotions is the most powerful way to connect with consumers. As it allows us to resonate deeply with individuals, stirring up feelings of joy, nostalgia, empathy, or excitement. Emotional campaigns can foster brand loyalty and drive consumer engagement.

Artificial Intelligence (AI) has made significant strides in the detection of emotions. Through the utilization of advanced algorithms and machine learning techniques, AI systems can analyze various signals and cues to discern human emotions.

State of the Art

Convolutional Neural Networks(CNN) are one of the most popular tools for classification, object detection and segmentation. This model is inspired by the human brain and how it processes visual information. The key idea behind CNNs is to learn and extract representations of visual features directly from the input data

Some advantages of using Convolutional Neural Networks for classification tasks, are:

They can capture complex visual patterns and hierarchies, enabling better understanding and interpretation of visual data.

They automatically learn and extract relevant features without any need for manual intervention.

They can identify and recognize objects in images regardless of their location or orientation.

They can be efficiently parallelized, taking advantage of GPUs and specialized hardware to accelerate training and inference.

Even though CNNs have many advantages, not every problem can be solved using them. The disadvantages of this model, are:

They can be computationally expensive to train and require substantial computational resources, such as high-performance GPUs.

They can be time-consuming when dealing with large datasets.

They required a large amount of labeled training data to effectively learn and generalize from patterns. Thus annotating such datasets can be time-consuming, expensive, or even infeasible in certain domains.

Limited training data can lead to overfitting or suboptimal performance.

Often function as black boxes, making it challenging to interpret why they make certain predictions or decisions.

Handling variable-sized inputs requires additional preprocessing which can add complexity to the model.

Dataset

The dataset used was found in Kaggle, it has more than 14000 images divided into angry, happy and surprised folders, happy contains 7215 images followed by angry with 3995 images and surprised with 3171 images, the size of each image is 48x48 pixels with 3 channels each one(RED,GREEN and BLUE)

Model

The model is conformed by 3 convolutional layers each one with a max pooling layer afterwards, a flatten layer and an output layer with softmax as activation function because it returns a probability vector which is what we expect in this multiclass classification problem.

Implementation

I loaded the data with a batch size of 32.

I verified the path displaying an image for each folder.

I print the shape of the image to see how many channels it has, the height and width.

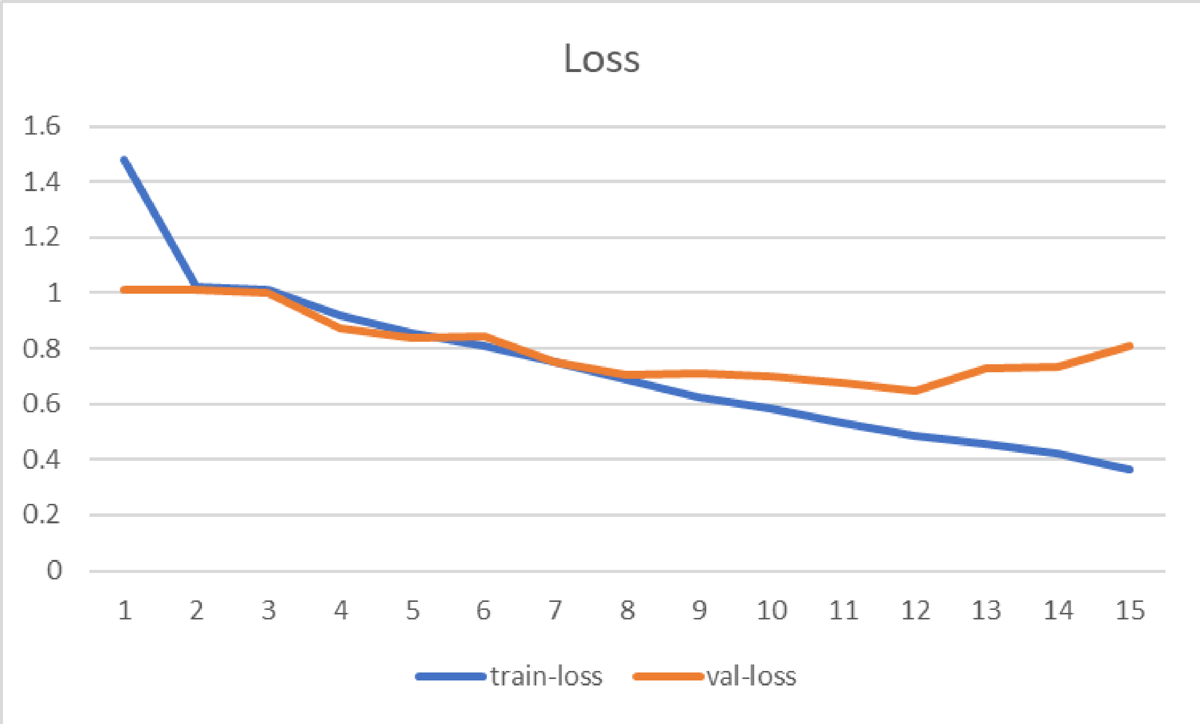
I splitted the data into training, validation, and testing, 70% 20% and 10% respectively.

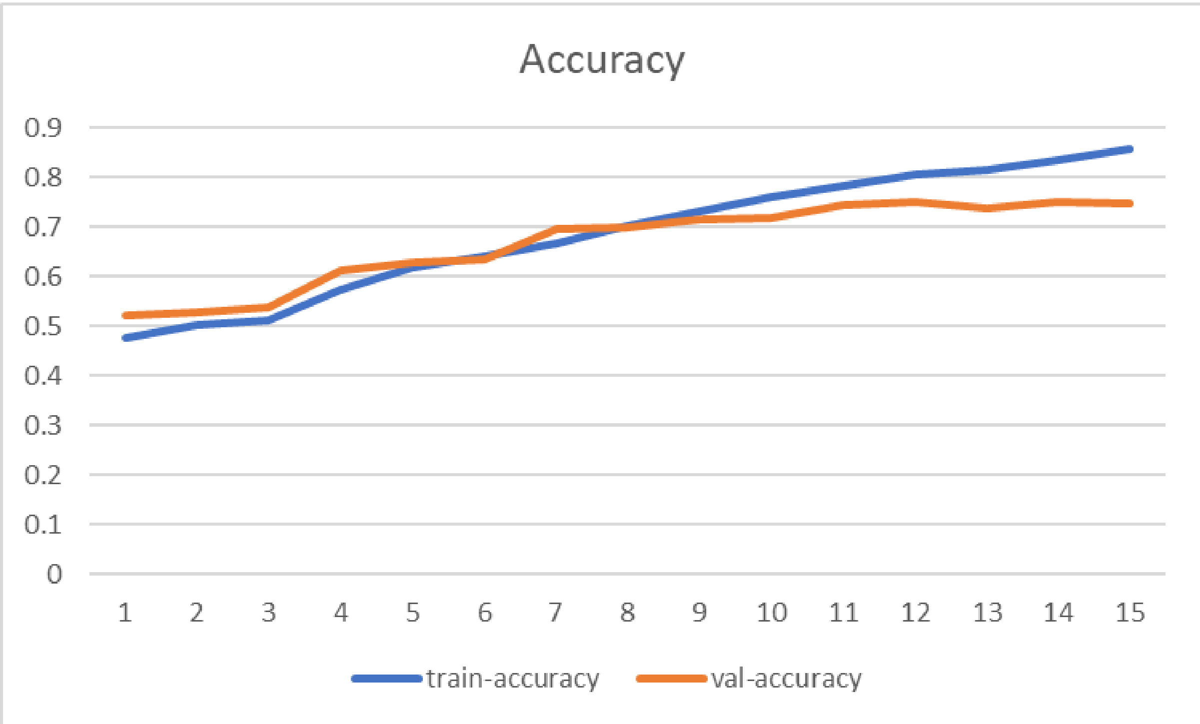
I created the model adding early stopping with a patience of 3.

At the end I predict emotions with images taken by me.

Evaluating Predictions

To evaluate the predictions of our model, I used tensorflow metrics getting a 79% of accuracy.





Conclusions

To conclude, the Convolutional Neural Network model developed to predict emotions has demonstrated a good accuracy. Nevertheless, it is important to note that while the achieved accuracy was great, further research and development needs to take place to enhance the model's robustness and generalization capabilities. Additionally, ongoing improvements to data collection and model architecture could further refine the model's performance, potentially pushing accuracy levels even higher.