Facial Emotion Recognition

This repository is my project hand-in for the AKT3 course on Deep Learning & Computer Vision.

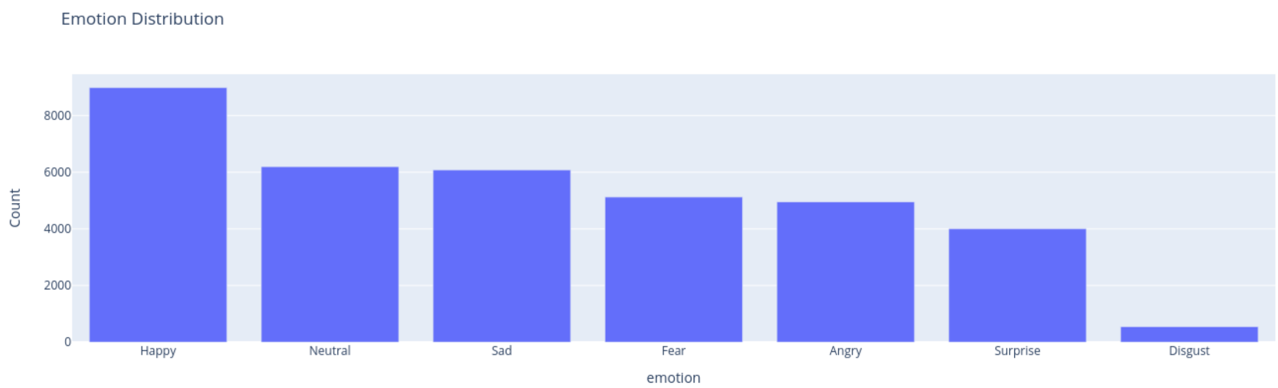
Dataset

For training this model we will be using the FER2013 dataset.

Example Data

The dataset contains 48x48 images of human faces.

Analysis



Using the distribution we can determine a baseline accuracy.

`HappyCounts / TotalCounts = 0.25`

`Baseline accuracy = 25%`

So by always guessing `Happy` we could reach an accuracy of 25%. Our goal is to improve that with the CNN.

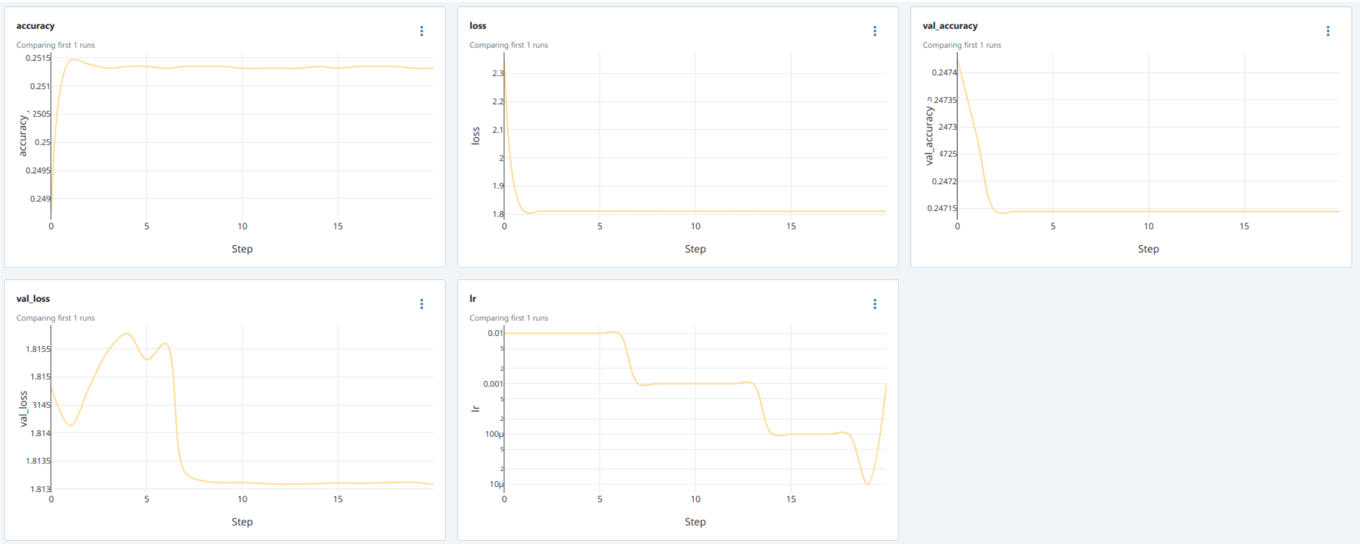
Baseline

Using the `train.py` script we are training a Facial emotion Recognition model that classifies images of human faces on 7 emotions (`"Angry", "Disgust", "Fear", "Happy", "Sad", "Surprise", "Neutral"`).

We split up the dataset into train, validation and test data.

- Train dataset size: 25120 examples
- Validation dataset size: 7179 examples
- Test dataset size: 3588 examples

Results



As shown in the graphs above we achieve very poor performance with our baseline parameters.

Parameter	Value
learning_rate	0.01
loss	categorical_crossentropy
epochs	50
batch_size	128
early_stopping_patience	7
lr_patience	5
lr_reduction_factor	0.1
optimizer	Adam
num_classes	7
input_shape	(48, 48, 1)
shuffle	True
restore_best_weights	True

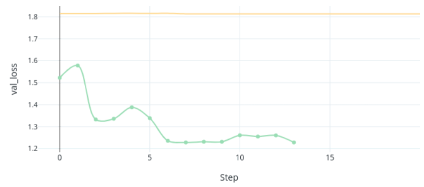
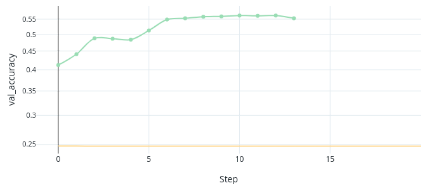
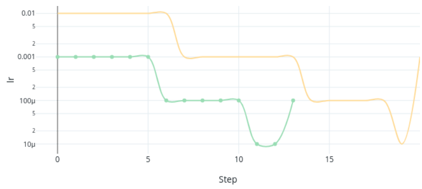
Experiment 1 - Improving validation-accuracy

In my first run the model only achieved a validation accuracy of 21% which is very poor. I was confused because other resources showed me that on this dataset significantly higher validation accuracies with similar CNNs could be achieved.

My hypothesis is that I chose a far to high starting learning rate which lead to very early convergence and therefore significant underfitting. By reducing the learning rate I expect better results.

Parameter	Value
learning_rate	0.001

Results

Validation Loss	Validation Accuracy	Learning Rate
		

As we can see in the resulting charts my hypothesis was correct and by reducing the learning rate we achieve much better results.

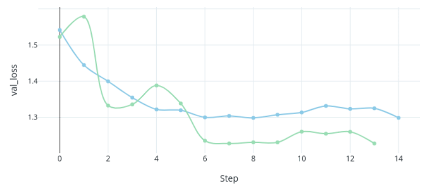
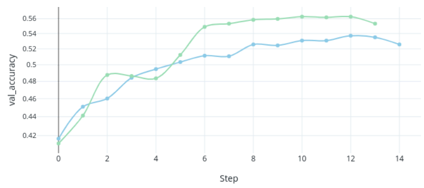
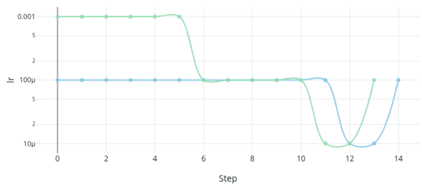
Experiment 2 - Smoothing the validation-loss curve

The new validation loss curve is very erratic. I want to make it smoother and reduce the bumpiness of the curve. For this I again will lower the learning rate by a factor of 10.

Parameter	Value
learning_rate	0.0001

Results

As we can see in the resulting charts my hypothesis was correct and by reducing the learning rate the curve is much less erratic.

Validation Loss	Validation Accuracy	Learning Rate
		

Experiment 3 - Disabling the restore-best-weights option

For some reason in the EarlyStopping callback the restore_best_weights option actually chooses a worse configuration of the model at the end. By disabling the option we want to prohibit that behaviour.

```
keras.callbacks.EarlyStopping(
                patience=params["early_stopping_patience"],
                restore_best_weights=False
            ),
```

Parameter	Value
restore_best_weights	False

Results

In the following graph we see that by disabling the `restore_best_weights` option we can actually keep the better model in the end.