Machine Learning Engineer Nanodegree

Capstone Project: Facial Keypoints Detection

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I. Definition

Project Overview

Facial Keypoints `(facial landmarks)` detection is an important and challenging problem in the field of **computer vision**, which involves detecting facial keypoints like centers and corners of `eyes`, `nose`, and `mouth`, etc. The problem is to predict the `(x, y)` real-valued coordinates in the space of image pixels of the facial keypoints for a given face image.

Facial features vary greatly from one individual to another, and even for a single individual there is a large amount of variation due to `pose`, `size`, `position`, etc. The problem becomes even more challenging when the face images are taken under different `illumination conditions`, `viewing angles`, etc.

Solving this problem that can provide the building blocks for several applications, such as:

- tracking faces in images and video
- analysing facial expressions
- detecting dysmorphic facial signs for medical diagnosis
- biometrics / face recognition

In the past few years, advancements in facial keypoints detection have been made by implementing **`Deep Convolutional Neural Networks (DCNN)**`.

Relevant academic research on this domain can be found in

- Facial Keypoints Detection
- Facial Key Points Detection using Deep Convolutional Neural Network - NaimishNet.

I chose this specific challenge because I currently work in the medical diagnosis field. I expect this project to help me understand facial keypoints recognition in a deeper way.

Datasets and Inputs

The data was acquired from the Facial Keypoints Detection `Kaggle` competition.

Data files

- `training.csv`: list of `7049 training images`. Each row contains the (x, y) coordinates for 15 keypoints, and image data as row-ordered list of pixels.
- `test.csv`: list of `1783 test images`. Each row contains ImageId and image data as row-ordered list of pixels

Problem Statement

The objective of this project is to accurately predict the facial keypoints (facial landmarks) of a face image. My hypothesis is, that this prediction can be performed based on a training set containing accurate facial keypoints, through a regression approach.

A `Convolutional Neural Network` (`CNN`) will be applied to predict the facial keypoints. A `CNN` was chosen for this problem because:

- This is a computer vision problem that requires capturing features for prediction
- CNNs are very useful in capturing features in images
- The expected responses (coordinates) make this a regression problem

A simple `Multilayer Perceptron (MLP)` will be used as a baseline model for comparison.

Metrics

The metric used to measure performance of the model i `Root Mean Squared Error` (`RMSE`):

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2}$$

`RMSE` is very common and is a suitable general-purpose error metric in regression problems. Compared to the `Mean Absolute Error`, `RMSE` punishes large errors.

Network Strategy

- Data augmentaion will be included if results are not satisfactory
- The network's artitecture is as follows:
  - Input layer
  - Convolution layers
  - Max Pooling layers
  - Batch Normalization layers
  - Fully Connected layers
  - Dropout layers
  - Prediction layer

II. Analysis

Data Exploration

Each predicted keypoint is specified by an (x,y) real-valued pair in the space of pixel indices. There are 15 keypoints, which represent the following elements of the face:

`left_eye_center`	`right_eye_center`	`right_eye_center`
`left_eye_inner_corner`	`left_eye_outer_corner`	`right_eye_inner_corner`

`left_eyebrow_inner_end`	`left_eyebrow_outer_end`	`right_eyebrow_inner_end`
`right_eyebrow_outer_end`	`nose_tip`	`mouth_left_corner`
`mouth_right_corner`	`mouth_center_top_lip`	`mouth_center_bottom_lip`

- *Left and right here refers to the point of view of the subject*
- *In some examples, some of the target keypoint positions are misssing (encoded as missing entries in the csv, i.e., with nothing between two commas)*
- *The input image is given in the last field of the data files, and consists of a list of pixels (ordered by row), as integers in (0,255). The images are 96x96 pixels*

Exploratory Visualization

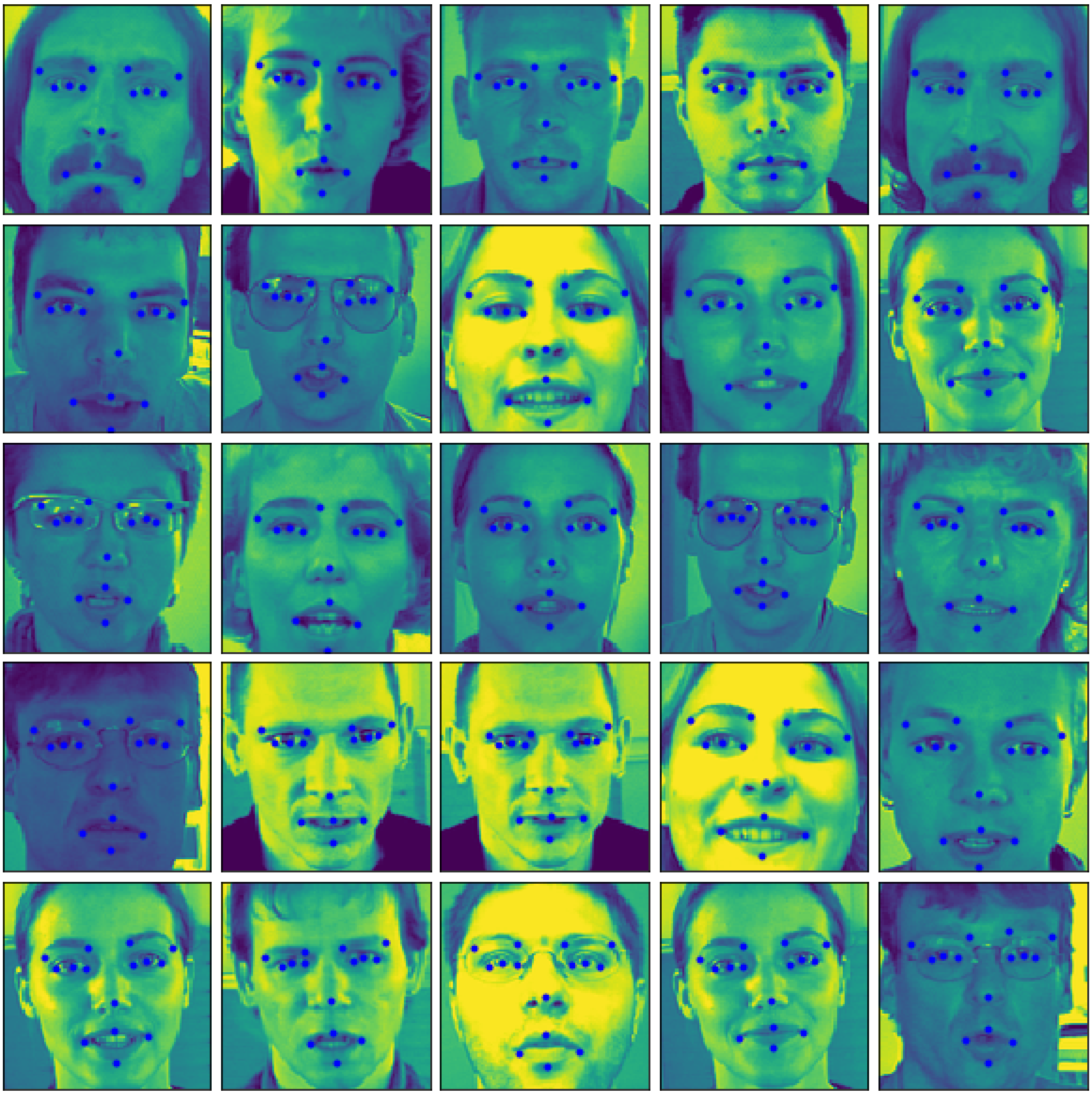
The data is summarized as follows.

```
Data columns (total 31 columns):

left_eye_center_x            7039 non-null float64
left_eye_center_y            7039 non-null float64
right_eye_center_x           7036 non-null float64
right_eye_center_y           7036 non-null float64
left_eye_inner_corner_x      2271 non-null float64
left_eye_inner_corner_y      2271 non-null float64
left_eye_outer_corner_x      2267 non-null float64
left_eye_outer_corner_y      2267 non-null float64
right_eye_inner_corner_x     2268 non-null float64
right_eye_inner_corner_y     2268 non-null float64
right_eye_outer_corner_x     2268 non-null float64
right_eye_outer_corner_y     2268 non-null float64
left_eyebrow_inner_end_x     2270 non-null float64
left_eyebrow_inner_end_y     2270 non-null float64
left_eyebrow_outer_end_x     2225 non-null float64
left_eyebrow_outer_end_y     2225 non-null float64
right_eyebrow_inner_end_x    2270 non-null float64
right_eyebrow_inner_end_y    2270 non-null float64
right_eyebrow_outer_end_x    2236 non-null float64
right_eyebrow_outer_end_y    2236 non-null float64
nose_tip_x                   7049 non-null float64
nose_tip_y                   7049 non-null float64
mouth_left_corner_x          2269 non-null float64
mouth_left_corner_y          2269 non-null float64
mouth_right_corner_x         2270 non-null float64
mouth_right_corner_y         2270 non-null float64
mouth_center_top_lip_x       2275 non-null float64
mouth_center_top_lip_y       2275 non-null float64
mouth_center_bottom_lip_x    7016 non-null float64
mouth_center_bottom_lip_y    7016 non-null float64
Image                        7049 non-null object

dtypes: float64(30), object(1)
```

Also, below is an example group of images.



Algorithms and Techniques

For this problem, I will use a **`Convolutional Neural Network (CNN)`**: In this, will use a Sequential (there's only a single input) model With 3 different `Conv2D` layers each having a `max pooling` layer having a `pool size` and `stride` of (2, 2). Each layer I have also added `batch normalization` and `dropouts` to mitigate overfitting. At the end, I have also added 3 `fully connected` layers With `dropouts`. In this, have used `adam` optimizer having `epochs` set to 100 and a `batch size` of 128.

This is the model's summary:

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 96, 96, 16)        80
_________________________________________________________________
dropout_2 (Dropout)          (None, 96, 96, 16)        0
_________________________________________________________________
```

```
max_pooling2d_1 (MaxPooling2 (None, 48, 48, 16)        0
_________________________________________________________________
batch_normalization_1 (Batch (None, 48, 48, 16)        64
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 44, 44, 32)        12832
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 22, 22, 32)        0
_________________________________________________________________
dropout_3 (Dropout)          (None, 22, 22, 32)        0
_________________________________________________________________
batch_normalization_2 (Batch (None, 22, 22, 32)        128
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 18, 18, 64)        51264
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 9, 9, 64)          0
_________________________________________________________________
batch_normalization_3 (Batch (None, 9, 9, 64)          256
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 7, 7, 128)         73856
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 3, 3, 128)         0
_________________________________________________________________
dropout_4 (Dropout)          (None, 3, 3, 128)         0
_________________________________________________________________
batch_normalization_4 (Batch (None, 3, 3, 128)         512
_________________________________________________________________
flatten_1 (Flatten)          (None, 1152)              0
_________________________________________________________________
dense_4 (Dense)              (None, 500)               576500
_________________________________________________________________
dropout_5 (Dropout)          (None, 500)               0
_________________________________________________________________
dense_5 (Dense)              (None, 128)               64128
_________________________________________________________________
dropout_6 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_6 (Dense)              (None, 30)                3870
=================================================================
Total params: 783,490
Trainable params: 783,010
Non-trainable params: 480
```

Benchmark

The benchmark Multilayer Perceptron `(MLP)`: In this, will use a `sequential` model With 3 different layers followed by an activation function `Relu`, and will also add a `dropout` after the first layer. I have used `SGD` optimizer for this using 50 `epochs` and a b`atch size` of 128.

This is the model's summary:

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 256)               2359552
_________________________________________________________________
activation_1 (Activation)    (None, 256)               0
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               32896
_________________________________________________________________
activation_2 (Activation)    (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 30)                3870
=================================================================
Total params: 2,396,318
Trainable params: 2,396,318
Non-trainable params: 0
```

III. Methodology

Data Preprocessing

Various operations were performed on the data for training.

- Convert the image values to numpy arrays (The `Image` column has pixel values separated by spaces)
- Drop all rows that have missing values in them
- Scale all pixel values to `(0, 1)` (normalize)
- Scale target coordinates to `(-1, 1)`
- Shuffle train data to mitigate overfitting

Implementation

The implemented models are baseline model (`MLP.h5`) and the final model (`CNN.h5`).

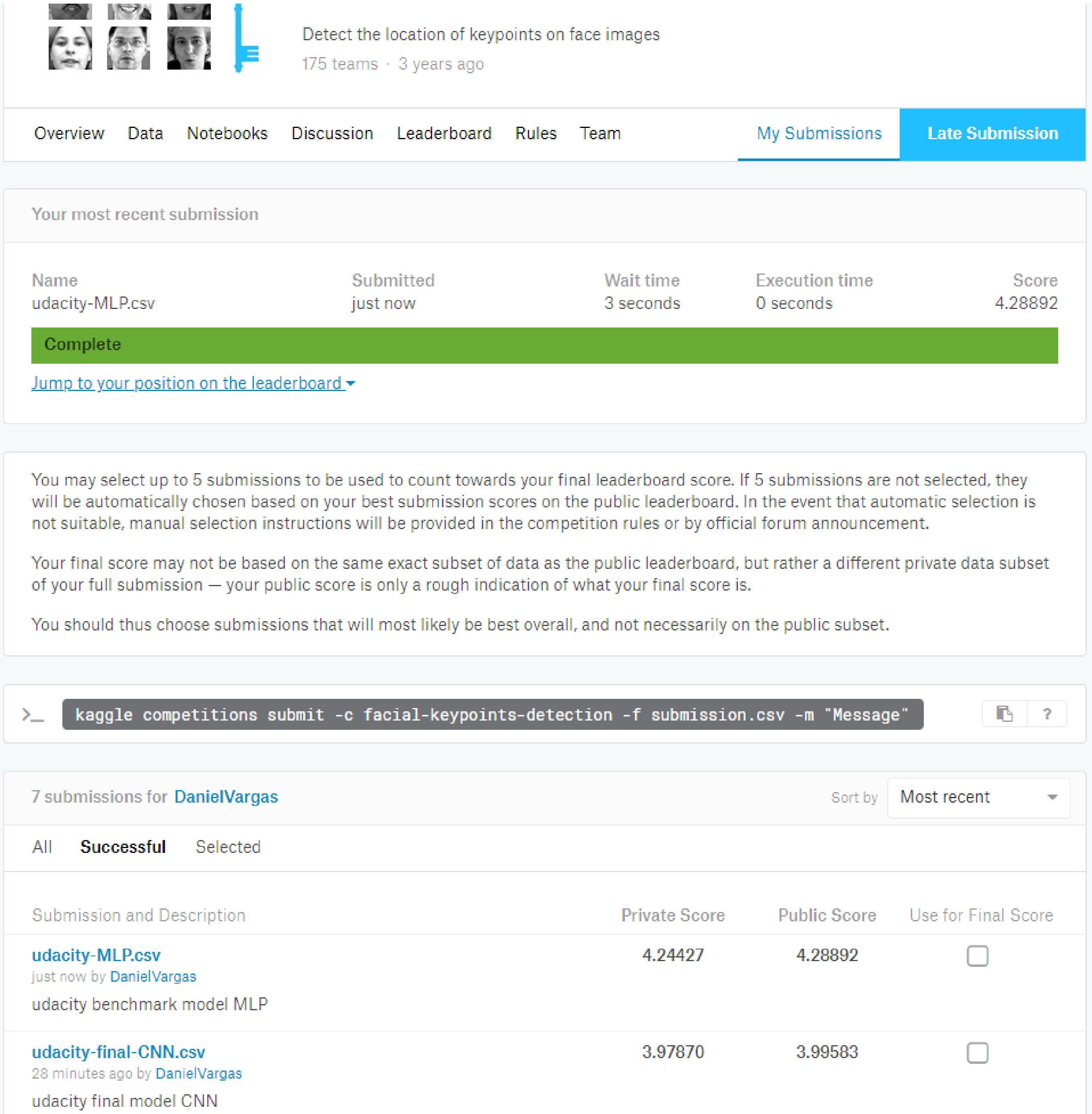
IV. Results

Model Evaluation and Validation

The final model was evaluated with the dataset provided in **Kaggle** and tested by submitting the results to the competition.

Model	Private Score	Public Score
Baseline model (`MLP.h5`)	4.24427	4.28892
Final model (`CNN.h5`)	3.97870	3.99583

Below, there's a screenshot of the submissions.



Justification

Based on the score results from **Kaggle**, the final model (`CNN.h5`) performed better than the benchmark model (`MLP.h5`) on the test set.

V. Conclusion

Reflection

The following steps were taken to complete this process:

1. Downloaded the dataset from kaggle
2. Perfomed data preprocessing
3. Trained a baseline model for comparison (`MLP.h5`)
4. Trained a final model for implementation (`CNN.h5`)

5. Converted the results to `.csv` and submitted them to score them on **Kaggle**
6. Chose the best model based on the models' individual scores

I learned a lot from this project:

- The importance on investing the time to prepare the data the right way to have a smooth training
- The importance of having in mind that the model might be implemented, taking into account not only metrics, but also prediction performance

Improvement

There are many ways in which the final model can be improved. The trade-offs of these improvements would depend on the final purpose o f the model.

- Perform hyperparameters optimization (e.g. random search, bayes optimization)
- Perform random image augmentation on the training set (e.g. rotations, translations, zoom-in, zoom-out, blur, etc.)
- Quantize the final model before conversion to reduce size and prediction speed