Machine Learning Engineer Nanodegree

Capstone Project

Nicholas Low
April 25, 2017

I. Definition

Project Overview

Facial keypoints detection is a field of study that has been relevant for many years due to its potential in creating a non-invasive method of identifying points on a face that can be used to determine any number of details about a person. However, facial features can differ greatly on individuals due to many variations of conditions in gathering images of individuals; therefore, determining accurate information from these features can prove to be difficult.

A well-known beginning to facial recognition systems is due to Tuevo Kohonen, a Finnish academic, who explained that a neural network could perform facial recognition only on aligned and normalized face images utilizing eigenvectors eventually becoming known as eigenfaces seen in Figure 1 [1]. These eigenfaces are representations of what the average face may look like based on a large set of data and allow a computer to determine what parts of the face generally look like. In modern facial keypoints detection, eigenfaces still exist as a primary method of identifying parts of the face although the science has become much more advanced.

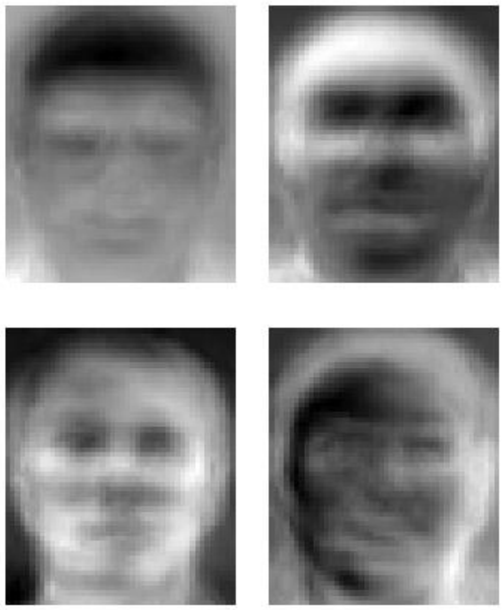


Figure 1: Example of Eigenfaces

By improving the method of facial keypoints detection systems, a number of solutions can occur. People may utilize these systems for lie detectors, medical diagnosis, biometrics, etc. On a bigger scale, every person may eventually have their own Sherlock Holmes, without the personality accompanying it (At least in the show "Sherlock"), to deduce the truth behind the many clues that exist within one's face.

The data set that will be used for this problem can be found at https://www.kaggle.com/c/facial-keypoints-detection/data.

Problem Statement

The problem to be solved is to predict keypoint positions/locations on face images. The goal is to predict the areas and parts where the mouth, eyes, ears, and nose are for all images with high accuracy. By determining the positions of these keypoints, a machine can gather information about the face. This will be a regression supervised learning problem as the data set includes labeled training data that uses continuous values in the form of pixels to learn from. A potential way to solve the facial keypoints detection problem is to utilize neural networks. The strategy to achieve the desired solution will be:

1. Attempt to filter unnecessary pixels in the image

2. Preprocess outliers by determining quartiles

3. Apply linear regression and determine errors for benchmark model
4. Apply neural network and determine errors to compare to benchmark
5. Utilize k-fold and Grid search cross-validation to ensure the model generalizes to new data in the most optimal way

Metrics

The evaluation metric that will be used to quantify performance of both models is going to be the root mean squared error. The root mean square error is relevant for this problem because it increases the error when the prediction is further away from the true value much more than other error metrics. Therefore, it is more important to have accurate values when using root mean squared error. The root mean square error is the average distance of a data point from the fitted line which will help determine the generalization of the models to new data.

There will be 30 errors displayed for each model representing the spread in the values of the output compared to the model. The errors will be found by determining each of the predicted keypoints' deviation from their actual values, squaring these values, averaging the squared values, and then taking the square root. Mathematically, each of the errors will be determine by the equation:

$$RMSErrors = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}$$

Figure 2: Root Mean Square Error Equation

II. Analysis

Data Exploration

The details of the dataset to be used in this model were taken from Kaggle's Facial Keypoints Detection competition [2]. The 15 keypoints, to be expected as outputs, being considered that represent elements in the face where left and right refer to the point of view of the subject are:

left_eye_center, right_eye_center, left_eye_inner_corner, left_eye_outer_corner, right_eye_inner_corner, right_eye_outer_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.

Each data point for these elements is specified by an (x,y) real-valued pair in the space of pixel indices. Data points that are missing are left blank. The input image is displayed in the last field of the datasets consisting of a list of pixels (ordered by row), as integers between (0,255). A sample of this data set is described in Table 1:

Table 1: Sample of Data Features

left_eye_center_x	left_eye_center_y	Image
66.03356	39.00227	… 238 236 237 238 240 240 239 241 241 243 240 239 231 212 190 173 148 122 …

There are 7049 images in the training set and 1783 images in the testing set and each of these images are 96x96 pixels.

The statistics that were calculated to examine the dataset are the minimum, maximum, mean, median, and standard deviation of the 15 keypoints' x and y values. The statistics will be displayed as in Figure 3:

```
Statistics for left_eye_center_x
Minimum pixels: 22.7633446452
Maximum pixels: 94.68928
Mean pixels: 66.3590212448
Median pixels: 66.4975659574
Standard deviation of pixels: 3.447988302
```

Figure 3: Sample of Statistics Data

The rest of the statistics can be viewed in the code.ipynb file associated with this project under the Data Exploration section. Based on the calculated statistics, there must be outliers in all the keypoints considering standard deviation is fairly small for all the keypoints and the maximum and minimum seem fairly outside the range of the mean. The median and mean are fairly equal for all keypoints. The largest difference between the median and mean is for right_eye_outer_corner_y with a difference of approximately 0.1664; therefore, the data is neither skewed to the right nor the left.

There are also 4909 missing values in the dataset which may make the row of data irrelevant where there is a missing value unless that missing value is also missing its x,y pair.

Exploratory Visualization

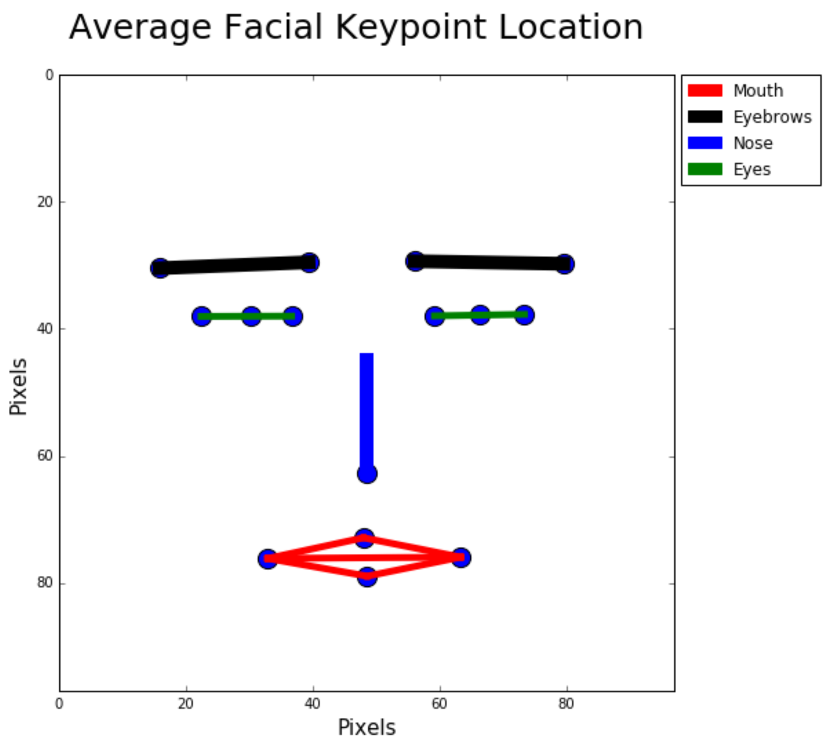


Figure 4: Visualization of Facial Keypoints

Figure 4 depicts a visualization of an average person's facial keypoints locations. Lines were drawn to visualize the keypoints better and give an idea of what they would look like on an image. This current iteration uses all the data points which consist of possible outliers.

The average mouth looks to be in an area that proportionally fits where a human mouth might be. The upper lip (47.98, 72.91) is above the lower lip (48.57, 78.97) and the corner of the mouth are to the right (32.90, 76.18) and left (63.29, 75.97) of the upper/lower lip. The tip of nose is at (48.37, 62.72) pixels which in Figure 4 is in a probable location for a nose. The center of the left eye is at (66.36, 37.65), the inner corner of the left eye is at (59.16, 37.94), and the outer corner of the left eye is at (73.33, 37.70). The right eye is in similar areas except mirrored on the opposite side; however, the face is not completely symmetrical.

Algorithms and Techniques

The benchmark model will be made with a linear regression model. A concept of a linear regression model can be defined as a using training points, pixels, to determine the best fitted line as depicted in Figure 5. By determining this line, a model can make a prediction on which pixel on a new image is the facial keypoint based off the margin of error from the line. The smaller the margin of error the more likely it is to be the correct pixel assuming a best fitted line. Due to the simplicity of the model, a linear regression is a suitable benchmark model for comparing solutions.

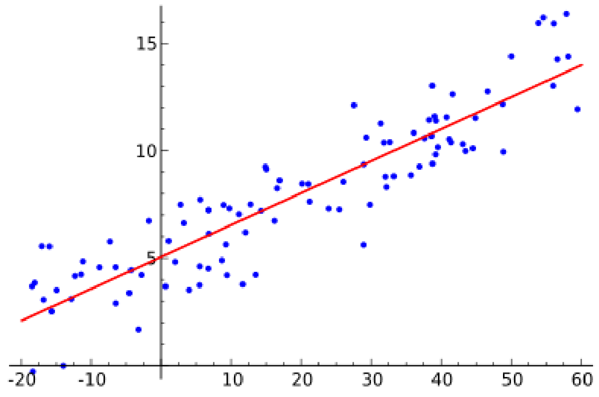


Figure 5: Linear Regression Example

The model this project will utilize to solve the problem is a neural network regressor. The traditional neural network, as seen in Figure 6, is a machine learning model where inputs get sent through a set of neuron layers, update weights based on optimizer functions, and determine outputs based off the weights. The activation functions that help determine the outputs is determined during the training phase where rectifier activation functions are typically used. The output of this network will then be used to determine the root mean squared error to compare to the benchmark model and other neural network.

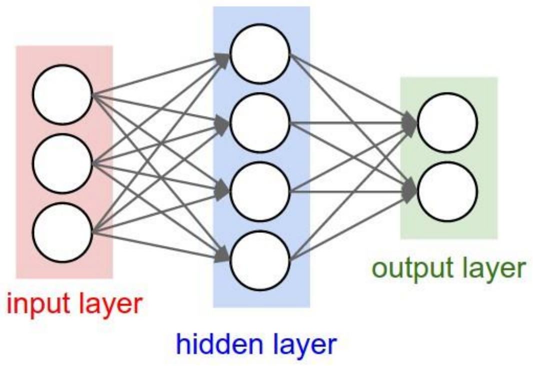


Figure 6: Neural Network Example

The traditional neural networks has a number of default parameters that will be used. All parameters were set to default except for a few parameters. These parameters are defined in the Keras library [3] as:

activation : Activation function for the layer.

input_shape: Dimensions of input.

batch_size : Size of minibatches for stochastic optimizers.

verbose : Whether to print progress messages to stdout.

learning_rate : Learning rate schedule for weight updates.

decay : Learning rate reduction per epoch.

optimizer: Algorithm for updating/determining weights.

A convolutional neural network is a neural network adjusted to process images more efficiently and accurately. If the traditional neural network does not satisfy the problem's requirements, a convolutional neural network may refine the neural network enough for a better result. A convolutional neural network makes the assumption that inputs are images which introduces properties that are encoded into the model. These properties are generally the width, height, and channels of the image. This allows the function to be more efficient and reduce the amount of parameters in the network.

The way a convolutional neural works is by sliding a filter of adjusted size over each section of an image. By utilizing matrix multiplication, this filter outputs a representation of a feature for each section to create an input feature map. Then the rectifier activation function is applied to create a rectified feature map as seen in Figure 7. This is considered the convolutional step. After this step, convolutional neural networks usually have a pooling step. The pooling step is used to reduce the complexity of each feature map by outputting the most important part of the map. Generally, the Max Pooling operation seen in Figure 8 is used by "taking the largest element from the rectified feature map" within a specified window. These two major steps are used multiple times to extract features and reduce complexity of the data set to train and output data seen in Figure 9.

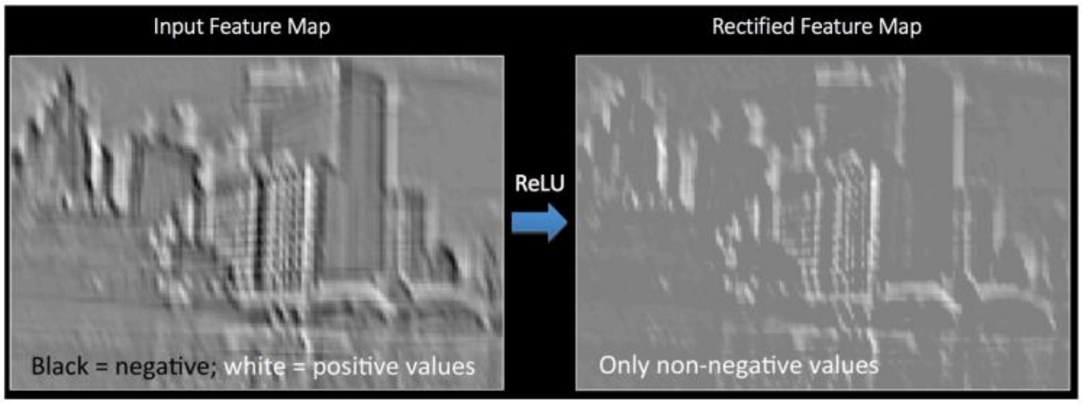


Figure 7: Rectified Feature Map Operation

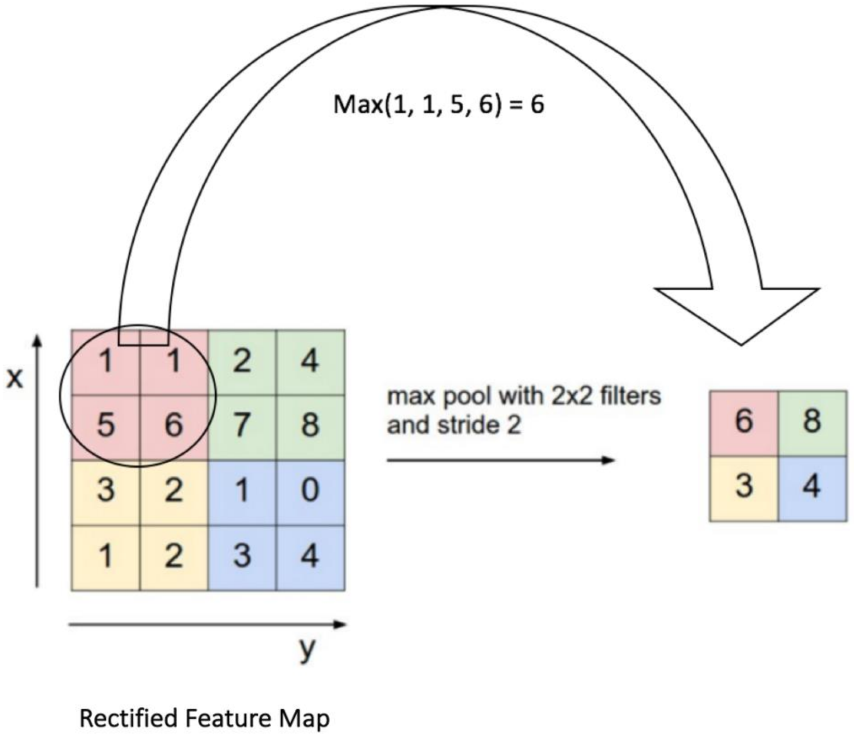


Figure 8: Max Pooling Step

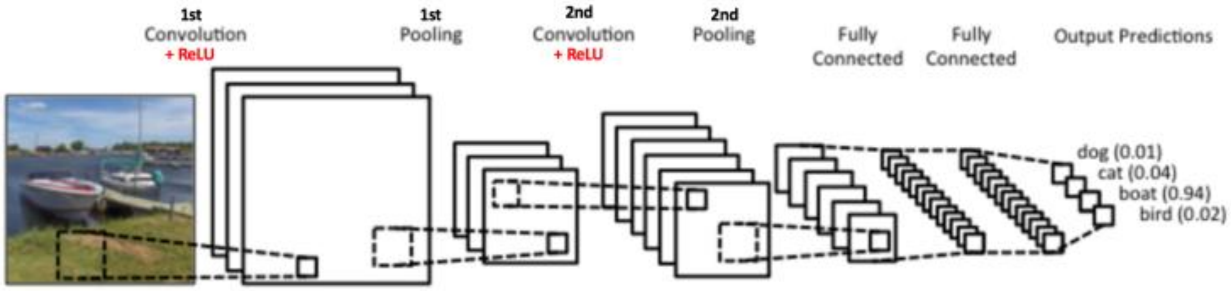
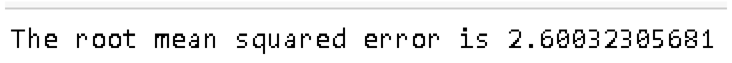


Figure 9: Classification Convolutional Neural Net Steps

After the initial training and error testing using the root mean squared error equation discussed in the Metrics section, the solutions will be maximized by testing with grid search cross-validation. Grid search cross-validation will be a technique to find the best set of parameters to use in the neural network by iterating through all possible combinations of parameters. The technique will then apply the neural network models to each combination and determine the combination with the least error which will be the final solution.

Benchmark

The benchmark model is a linear regression model utilizing the sklearn library. The error values display the accuracy of the predicted values where 0 is the absolute best possible value. Considering 2.6, seen in Figure 7, is not extremely close to 0, this model is clearly not the best model and can be used as a benchmark to improve upon. This value will be useful in comparing possible solutions as neural network's validation loss is outputted in average mean squared error which can be used to calculate the average root mean squared error.



```
The root mean squared error is 2.60032305681
```

Figure 10: Average RMSE Linear Regression

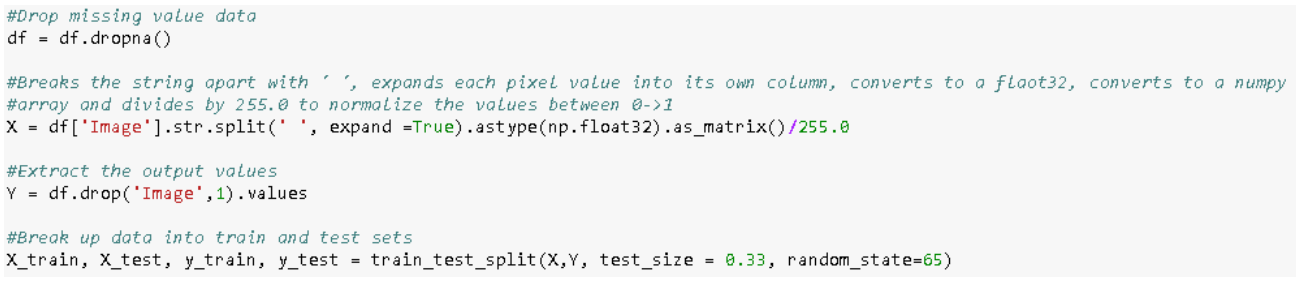
III. Methodology

Data Preprocessing

Figure 6 depicts the code utilized to preprocess the data. First, the data had several issues regarding its usability. Null values exist for 4909 values in the data set. Data could not be fitted without dealing with the null values. Considering transforming the null values into another value would affect results, the best option was to just remove them using dropna().

The data also needed to convert training image data, X_train, into something the sklearn Linear Regression Model could recognize. Therefore, the data was expanded to split the string for each image into separate columns using the expand option in str.split(), converted all the strings into floats with astype(float), and then converted into a numpy matrix with as_matrix(). X_test was much easier as the contents were recognized as integers by Python, so the values were just extracted with Pandas' values function.

The data set had to be split into training and test sets as the test set provided by Kaggle does not have any true results. 1/3 of the training set was converted into a test set in order to provide a large enough data set for training the model.



```
#Drop missing value data
df = df.dropna()

#Breaks the string apart with ' ', expands each pixel value into its own column, converts to a float32, converts to a numpy
#array and divides by 255.0 to normalize the values between 0->1
X = df['Image'].str.split(' ', expand =True).astype(np.float32).as_matrix()/255.0

#Extract the output values
Y = df.drop('Image',1).values

#Break up data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,Y, test_size = 0.33, random_state=65)
```

Figure 11: Preprocessing Code

Implementation

The implementation of the solution to the problem was done through the use of neural networks. The neural network was created utilizing the Keras library. This neural network has three layers total: input, hidden, and output similar to Figure 12. The input layer would receive the training data and learn over 400 iterations which was determined after multiple attempts to find where it converges to its best root mean squared error value. Figure 13 depicts the code and the initialization of the neural network. This input layer was set up to have 1 input node to take in the 9216 pixels with a rectifier activation function. The hidden layer has 15 neurons with the rectifier activation function. Finally, the output layer has 30 neurons for each possible output and uses a linear activation function.

The difficulty in implementing the solution was understanding how neural networks were set up in Keras. Keras builds the neural networks per layer. Each layer has a large set of parameters to choose from and learning how to differentiate between the input layer, hidden layer, and output layer required some research.

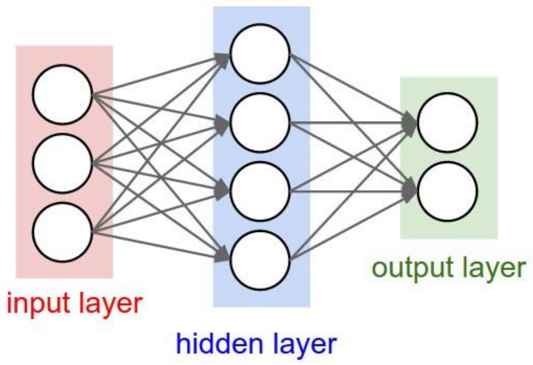
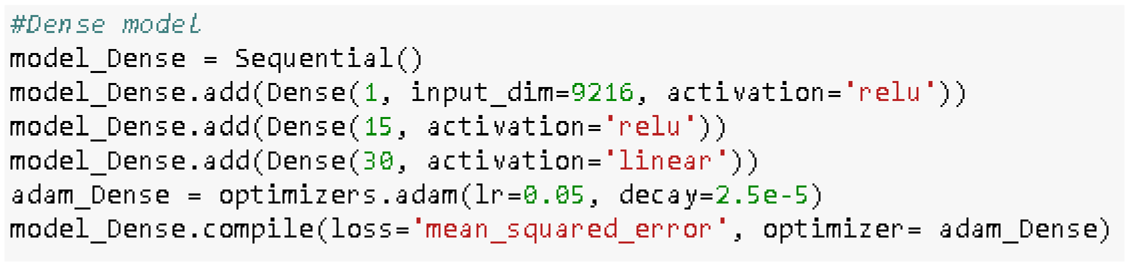


Figure 12: Example of Neural Network Layers

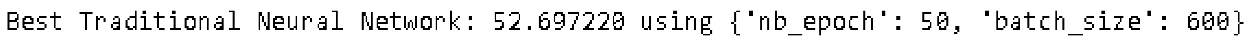


```
#Dense model
model_Dense = Sequential()
model_Dense.add(Dense(1, input_dim=9216, activation='relu'))
model_Dense.add(Dense(15, activation='relu'))
model_Dense.add(Dense(30, activation='linear'))
adam_Dense = optimizers.adam(lr=0.05, decay=2.5e-5)
model_Dense.compile(loss='mean_squared_error', optimizer= adam_Dense)
```

Figure 13: Dense Neural Net Code

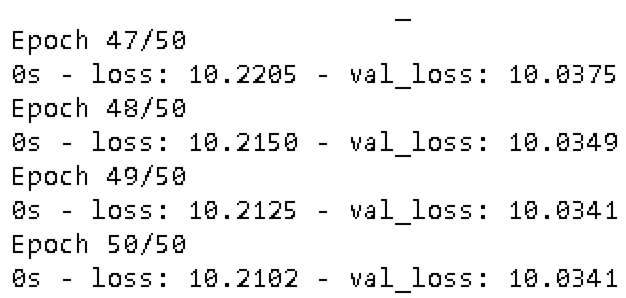
Refinement

The initial attempt at improving the neural network was to manipulate parameters to run more efficiently and accurately. I used Grid search cross-validation to check for a few parameters; however, the project was limited due to memory restraints. For the traditional neural network the parameters used were epochs and batch size. The Grid Search tested for [50,200] epochs and [50,200,600] batch sizes. Based on the Grid Search, the best traditional neural network had the greatest results at 50 epochs and 600 batch size as defined in Figure 14.



```
Best Traditional Neural Network: 52.697220 using {'nb_epoch': 50, 'batch_size': 600}
```

Figure 14: Grid Search Traditional Neural Network

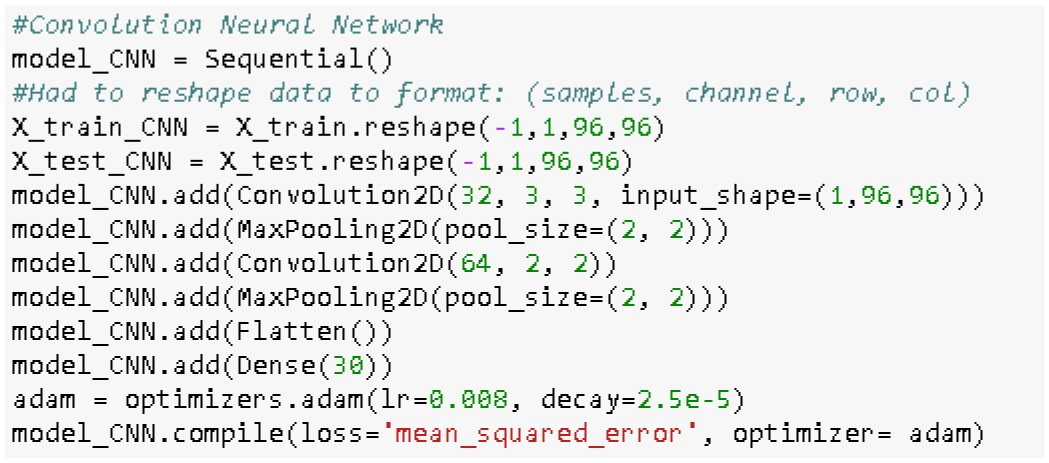


```
Epoch 47/50
0s - loss: 10.2205 - val_loss: 10.0375
Epoch 48/50
0s - loss: 10.2150 - val_loss: 10.0349
Epoch 49/50
0s - loss: 10.2125 - val_loss: 10.0341
Epoch 50/50
0s - loss: 10.2102 - val_loss: 10.0341
```

Figure 15: Traditional Neural Network Result

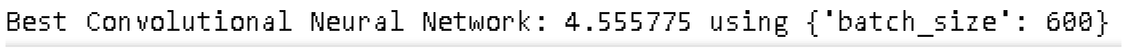
However, the traditional neural network did not result in a better root mean squared error score than the benchmark model with score of 3.17 as seen by taking the square root of the validation loss score in Figure 15. After researching the topic of utilizing images in neural networks, convolutional neural networks or CNNs came up as an altered neural network that creates models based off of image inputs more efficiently. The reason CNNs are better for images is that they make the assumption that inputs are images which introduces properties that are encoded into the architecture. These properties are generally the width, height, and channels of the image. This allows the function to be more efficient and reduce the amount of parameters in the network.

Figure 16 is the code implementation of a 2D convolutional neural network. The code consists of reshaping the data to a (1,1,96,96) form in the format (samples, channel, row, col), then running it through a set of convolutional layers that include pooling layers to reduce the size of data to process. Convolutional neural networks are much more memory intensive than traditional neural networks. Therefore, in using Grid search cross-validation, I could only test for variable batch sizes. The tested batch sizes were 200 and 600. Figure 17 shows the results of the grid search cross-validation where the 600 batch size was the most optimal netting an average of 2.13 root mean squared error. This root mean squared error is much better than the average of the traditional neural network by a large margin.



```python
#Convolution Neural Network
model_CNN = Sequential()
#Had to reshape data to format: (samples, channel, row, col)
X_train_CNN = X_train.reshape(-1,1,96,96)
X_test_CNN = X_test.reshape(-1,1,96,96)
model_CNN.add(Convolution2D(32, 3, 3, input_shape=(1,96,96)))
model_CNN.add(MaxPooling2D(pool_size=(2, 2)))
model_CNN.add(Convolution2D(64, 2, 2))
model_CNN.add(MaxPooling2D(pool_size=(2, 2)))
model_CNN.add(Flatten())
model_CNN.add(Dense(30))
adam = optimizers.adam(lr=0.008, decay=2.5e-5)
model_CNN.compile(loss='mean_squared_error', optimizer= adam)
```

Figure 16: Convolution Neural Net Code



```
Best Convolutional Neural Network: 4.555775 using {'batch_size': 600}
```

Figure 17: Grid Search Convolutional Neural Net

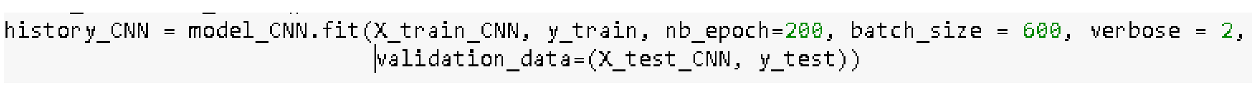
IV. Results

Model Evaluation and Validation

Utilizing the linear regression benchmark model and comparing between both neural network models, the convolutional neural network was determined to be the best model.

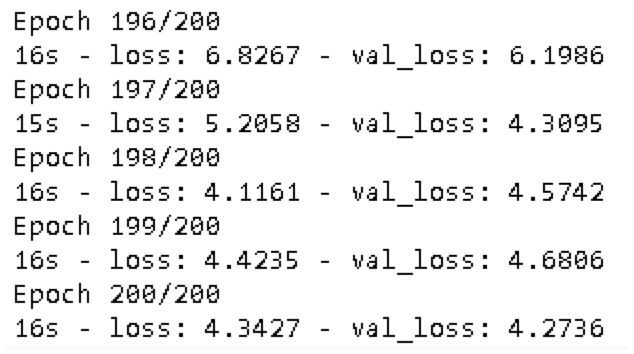
The final parameters for the model were determined after trial and error attempts, as well as, grid search cross-validation. Due to the memory constraints of the computer, the grid search cross-validation could only look through two different possibilities of batch size without crashing. The grid search cross-validation found that a batch size of 600 is the best as seen in Figure 17. Therefore, the final parameters are seen in Figure 12. The 200 epochs allow for some convergence of the validation results. This amount of epochs was also close to maximum amount allowed by the memory constraints as by 300 to 400 epochs, the computer would crash frequently.

The final model was also tested with a testing set to see how well it generalizes to new data. The test's result is noted in Figure 19 as val_loss which displays a value in the form of the mean squared error. At 200 epochs, the root mean squared error of the test set is 2.06 which is quite an improvement over the 2.6 of the benchmark model.



```
history_CNN = model_CNN.fit(X_train_CNN, y_train, nb_epoch=200, batch_size = 600, verbose = 2,
                            validation_data=(X_test_CNN, y_test))
```

Figure 18: Final Parameters of CNN



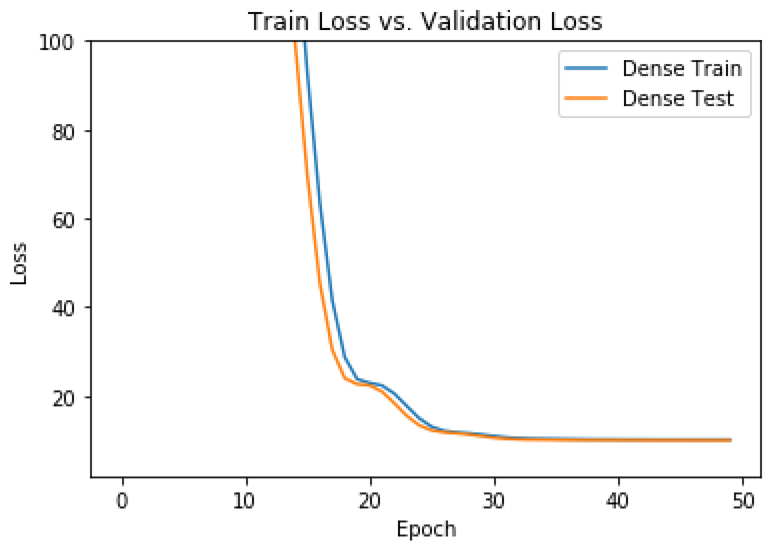
```
Epoch 196/200
16s - loss: 6.8267 - val_loss: 6.1986
Epoch 197/200
15s - loss: 5.2058 - val_loss: 4.3095
Epoch 198/200
16s - loss: 4.1161 - val_loss: 4.5742
Epoch 199/200
16s - loss: 4.4235 - val_loss: 4.6806
Epoch 200/200
16s - loss: 4.3427 - val_loss: 4.2736
```

Figure 19: Mean Squared Error of CNN

Justification

Out of the two models present in this paper, convolutional neural networks is the only one that beats the benchmark model which was the requirement to being a useful final solution. Also, the traditional neural network had an average root mean squared error of 3.17, as seen by the mean squared error score in Figure 15. Meanwhile, the convolutional neural network had an average root mean squared error score of 2.06. The final result of the model measured by the root mean squared error metric is 2.06 which is much better than the 2.6 average error of the linear regression model.

Figure 20 justifies the reasoning behind choosing the convolutional neural network as the best solution to the problem. The first plot displays the train loss vs validation loss of the traditional neural network. The plot has a much smoother learning curve that converges well; however, it only converges at approximately 10.0 mean squared error or 3.16 root mean squared error which is 0.56 worse than the benchmark model. On the other hand the second plot depicting the convolutional neural network has much more erratic learning curve; however, it converges at a much lower root mean squared of 2.06.



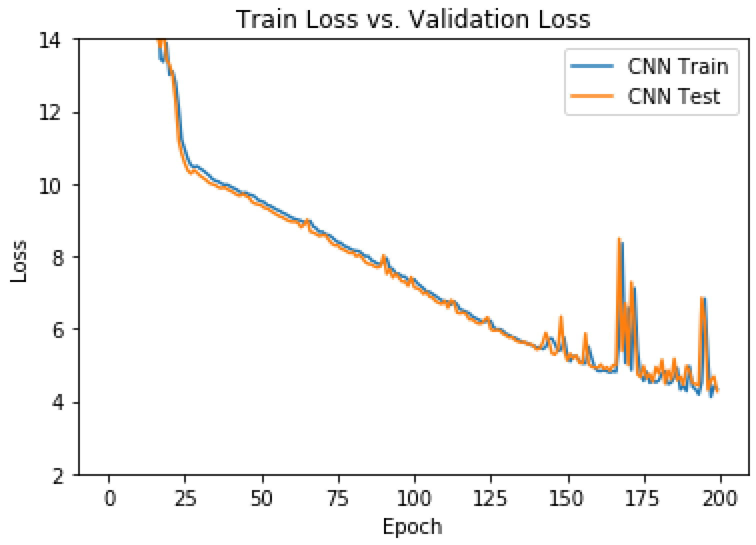


Figure 20: Train Loss vs Validation Loss Graphs

V. Conclusion

Free-Form Visualization

Figure 21 provides two images to represent the usefulness of the final model. These images were created by using the final model to predict points with the images as inputs. These predicted points were then placed back on the image to visualize an idea of how the model would be utilized to solve the problem of facial keypoints detection.

The final model used the 'adam' optimizer with a learning rate of 0.08 and a decay of 2.5e-5. The predicted points are not completely accurate which may be due to the somewhat high learning rate. This characteristic is evident as the root mean squared error is 2.06 and not 0.00. However, due to limitations of the computer, 0.08 was one of the better learning rates that would converge near 200 epochs. In both images, the four point locating the areas of the mouth have the largest difference from their true values. This is most likely from the mouth having the largest variation of sizes, shapes, and orientations. With a high learning rate, the variations may have caused fluctuations in the learning process which made the model have difficulties accounting for the differences in mouths.

However, considering the accuracy of the other facial keypoints and overall accuracy, the current state of the model looks capable of being a solution to the problem; however, there could be many improvements to the model.

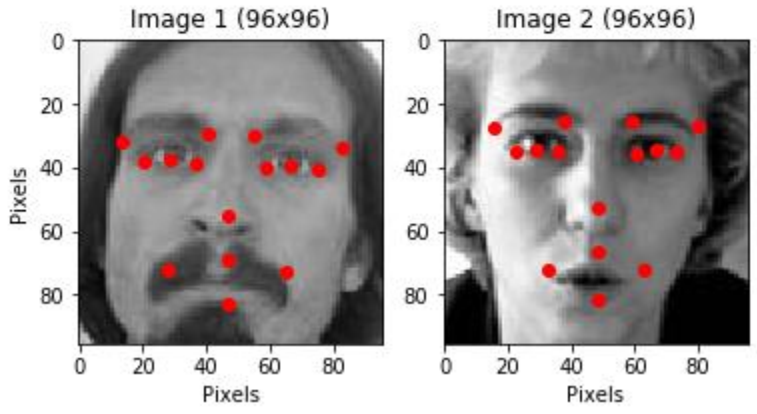


Figure 21: Sample Model Predictions

Reflection

The process for the project can be listed as followed:

1. Defining the problem statement, possible solutions, and determining the metric in which to determine how well the solution performs.

2. Preprocessed data by removing nans.

3. A linear regression benchmark model was created.

4. A traditional and convolutional neural network regressor was created.

5. A convolutional neural network regressor was created, trained, and tested.

6. A grid search cross validation was applied to determine an optimal set up for both models and find that the convolutional neural network was the better solution.

7. Both model were trained and tested using the optimal set up found by grid search cross validation.

Step 5 was both the most interesting and difficult aspect of the project. As the subject of convolutional neural networks was new, the difficulty was due to researching, determining, and creating a convolutional neural network with the Keras library and what each layer does to the dataset.

Learning the small and big nuances that define what a convolutional neural network is compared to a traditional neural network was the most interesting part of the project. The neural network's defining characteristics were the ability to input an image's specifications in the form of (samples, channel, row, columns) and utilize pooling filters to reduce the amount of computations the more complicated neural network needed to make.

Improvement

The project could use many improvements. These improvements could include getting a better computer that can process more data allowing the model to run higher iterations and test for more parameters in the grid search cross validation. They may also include gathering more data to prevent overfitting and to allow for other preprocessing techniques such as outlier detection. Another possible improvement could be to utilize a different algorithm such as support vector machines to predict facial keypoints; however, through research convolutional neural networks seem to be at the forefront of image recognition techniques.

However, an improvement to the algorithm that could possibly increase the potential of the model is the optimizer. Currently, the model is using the 'adam' optimizer with a learning rate of 0.08 and a decay of 2.5e-5. These parameters were determined to properly compare the traditional neural network and the convolutional neural network. However, by lowering the learning rate or changing the optimizer, the model could improve by having a steadier learning curve than Figure 15 depicts and could also improve accuracy.

Work Cited

[1] T. Choudhury, “History of face recognition,” 2000. [Online]. Available: http://vismod.media.mit.edu/tech-reports/TR-516/node7.html. Accessed: Jan. 10, 2017.

[2] Kaggle, “Data – Facial Keypoints Detection,” 2017. [Online]. Available: https://www.kaggle.com/c/facial-keypoints-detection/data. Accessed: Jan 11, 2017.

[3] “Keras: Deep Learning library for Theano and TensorFlow,” *Keras Documentation*. [Online]. Available: https://keras.io/. [Accessed: 20-Apr-2017].