Faceball

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Objectives

- *To determine if there is a correlation between facial features of Major League Baseball players and their performance.*
- *Accurately predict a player's projectability in the major league based solely on a headshot.*
- *Attempt to visualize the filters of the neural network.*
- *Produce an average depiction of each class of all the players to play the game.*

Facial Recognition

Pictures and basic stats of every American-born baseball player were scraped from baseball-reference.com. Once collected, these images were fed through facial detection to determine if a face was present. The facial detection looked for facial landmarks, and if found, cropped the original image into one representing the following:

Measures

The basic statistic used to measure a player's performance was WAR (Wins Above Replacement). A replacement is a AAA free-agent, meaning that a player of this caliber can be picked up at any time. A WAR of 0 indicates an average player. A WAR of 5 indicated a perennial all-star.

Neural Network

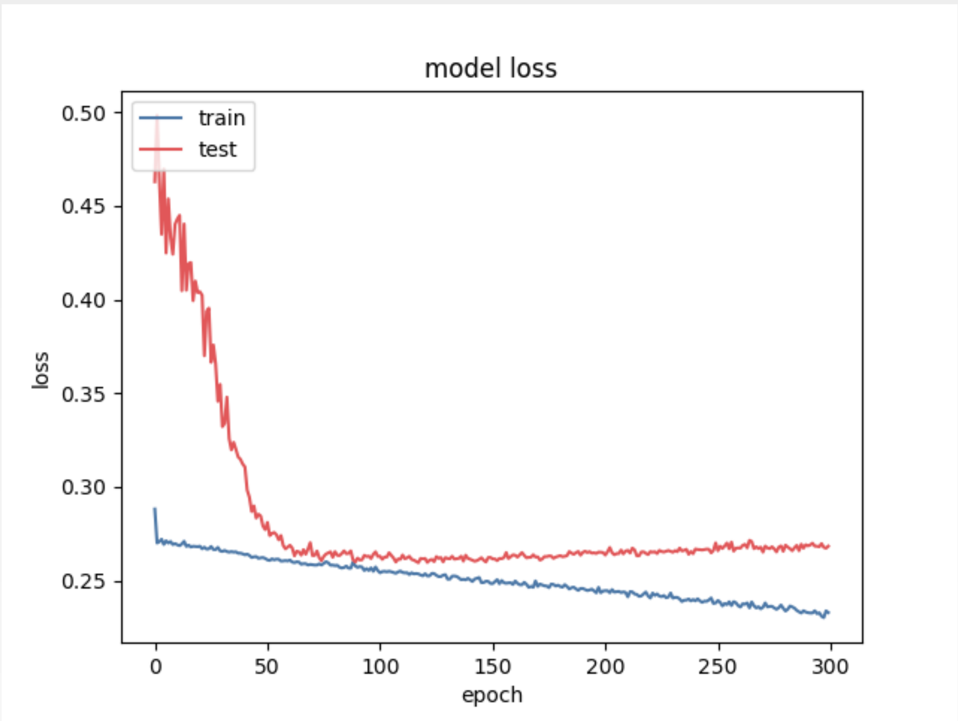
The processed images were fed through a convolutional neural network to see if there was a correlation between facial features and performance.

The model architecture can be described as:

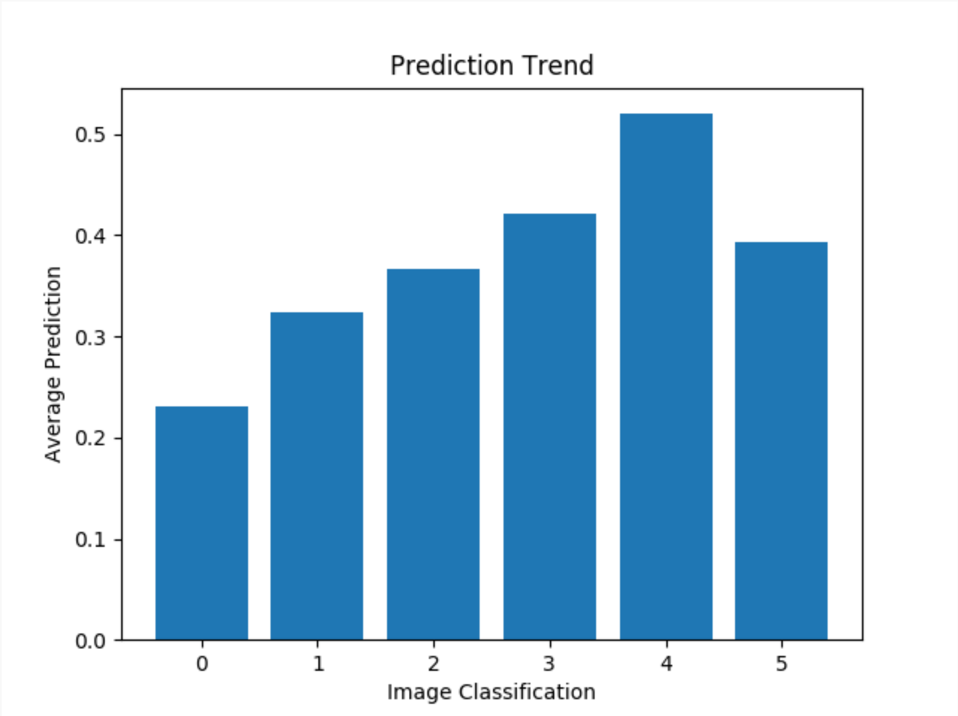
- *5 alternating convolution, max pooling, and dropout layers (0.35)*
- *4 fully connected layers*
- *Binary crossentropy loss, sigmoid output activation, adam optimizer*

Results

The model's ability to learn can be visualized by the following graph showing the training and test loss.

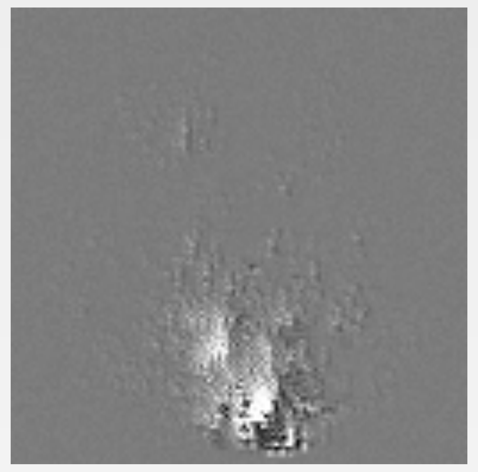


The average predictions for each class are presented below:



Filter Visualization

The images that are fed into the model have a very high amount of loss. The loss is reduced by gradient descent with respect to the cost function associated with the data. The picture is broken down piece by piece and the neural net learns the bits that make up the data. To visualize the filters you can think of the reverse of this process. You start with an output class, let's use 0, and feed a noisy image (think bad reception on a 1950s television) into the model. The model will employ gradient ASCENT in order to maximize the loss of the cost function. Each iteration of gradient ascent, the loss will increase and a picture representing what the model thinks to be a 0 will begin to take shape. Below is the output of a picture that the model is 99.9% certain to belong to the class 0.



PCA/Eigenfaces

The results of the principal component analysis and eigenfaces were can be seen in the pictures below.

Conclusion

Looking at the loss chart, the model continuously learns the training data as can be seen by the linear decrease in training loss. The test loss decreases rapidly until the 60th epoch, where it flattens out.

The model was able to predict on unseen data decently well. Once it got past predicting solely 0's, it began to pick out some features that were apparent amongst the different classes. This can be seen in the prediction trend chart.

Filter visualization was an interesting approach to try and see what the model was predicting on. However, the output images were not very interpretable to the human eye.

PCA/Eigenfaces allowed us to visualize the average faces for each class and interpret these results. The results of this part of the experiment are highly interpretable, however, it seems as though classes 4 and 5 show players with more sharp, defining features. Classes 0 and 1 depict a rounder face, possibly indicating that excess fat around the face reduces a player's chances of projecting well into the big leagues.

There seems to be a slight trend in facial features and performance, however, it is hard to explain what is actually driving the predictions. This project was more to prove the theory instead of explaining the reason why it is true.

References

1. baseball-reference.com