ISyE 6740 – Summer 2021
Final Project Report

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Project Title: Equine Facial Recognition (Team 138)

Problem Statement

Identification of horses can prove difficult for veterinary personnel or in a show setting, particularly if the horses are kept in a pasture and not individual stalls. Microchipping is becoming more common among horses [1], but additional equipment is required to read microchips and comparison to the number in the horse's file is performed manually. In a show setting this poses a challenge for confirming a horse's identity, and in the veterinary world a mix up could lead to the treatment of the wrong horse.

In addition to the previously mentioned applications, the United Stated Department of Agriculture (USDA) requires horses to pass health checks and blood tests for certain diseases before they can be transported between states or taken to locations with a large number of horses such as shows and rodeos. The forms and records for these health checks and blood tests include photos of the horse, so if the state had a database of horses and facial recognition capabilities, they could run the submitted forms through the system to confirm the horse identified on the documents matches the photographs submitted.

One final application would be in the sale of horses. In the western United States, it is required that a state official perform a 'brand check' in order to certify a horse is being legally sold. With a database of horses and facial recognition, it could help in this process to verify horse identities and ownership history.

With smart phones readily available, a facial recognition system could be used to identify horses quickly and easily with no additional equipment needed beyond the phone that most carry at all times.

This project will explore the ability to detect features on a horse to prepare photos for facial recognition, and then test if a facial recognition system can provide reliable results in an equine setting.

Data Source

Data for the face detection task was gathered from the HABIT Horse Project. This project has trained a classifier for detecting horse ears that was used to help with determining the region of interest in the horse images [2].

For training data, approximately 12 photos of 5 different horses were taken over multiple days to capture different lighting conditions and backgrounds. These were all collected using a smart phone camera which would be the tool utilized by end users of this model.

For testing data, one additional photo of the 5 horses from the training set was taken separately from the training data with no special care to make sure the head was straight or that the ears were up and forward. The goal of this was to simulate how a user of the model might find a horse in the field.

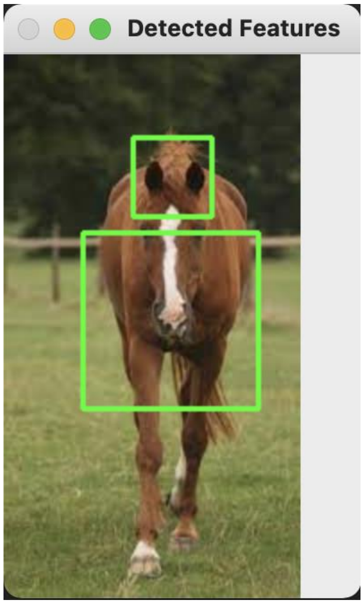
Methodology

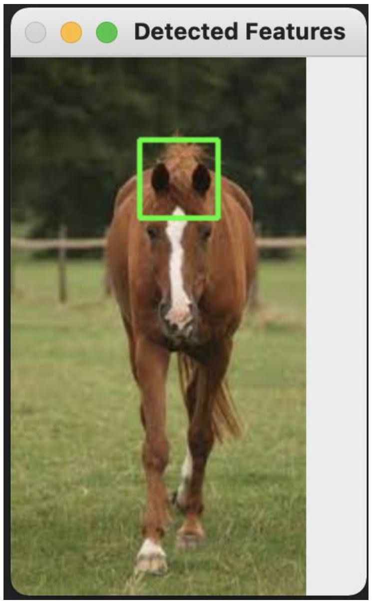
The OpenCV package (opencv.org) in Python 3 was used for computer vision tasks when building this project.

The first step in achieving equine facial recognition was to find a method to isolate the face of the horse to a 'region of interest'. To do this, the OpenCV package was used along with a Haar cascade classifier. This classifier uses AdaBoost to create a learning algorithm which can detect a small number of critical features from a larger set. [3]

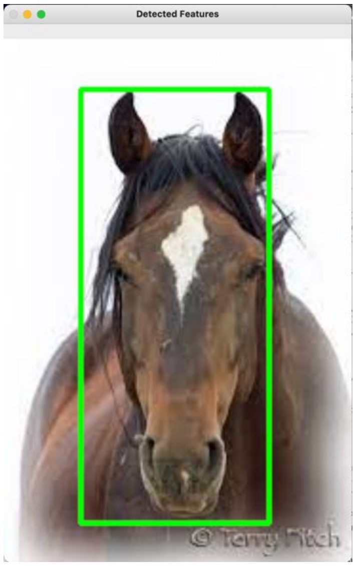
Several Haar classifiers are available in the OpenCV package when installed. These focus on human features and more common domestic animals, such as cats. Initially, the 'eye' classifier was used to see if it could recognize a horse's eye. The horse eye differed enough from the human eye that was used to train the model that a consistent detection was not achieved.

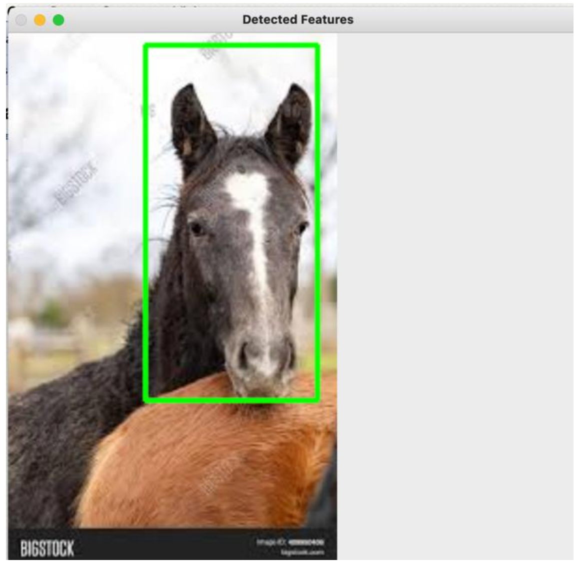
Although a custom classifier could be trained, a Haar cascade classifier that had been created to detect horse ears was found through the HABIT Horse Project. By detecting the horse's ears an upper boundary for the horse's head was created. Some tuning of the parameters of the Haar classifier was conducted on a variety of horse images to minimize instances of misdetection. The images below represent an initial model which was overly sensitive and prone to misdetection compared to the model after having parameters adjusted.





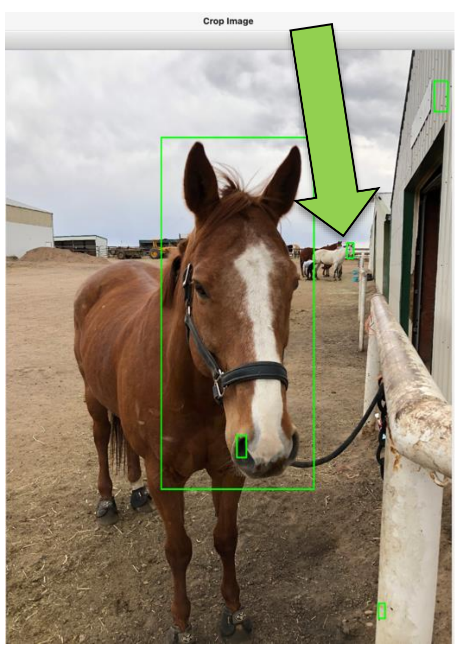
After the Haar classifier was set to reliably detect horse ears in a photograph, a general ratio of ear width to head height was determined by looking at images of several horses. This allowed for the entire face of the horse to be selected based on the location of the ears, as shown below.



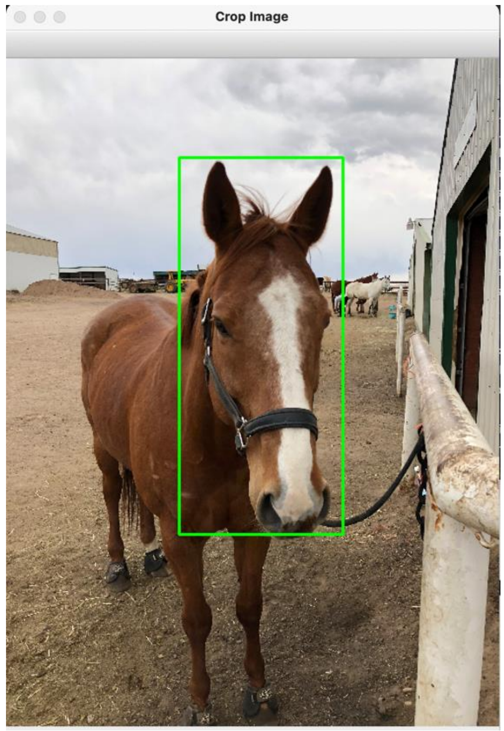


This technique was generally successful in creating a region of interest which included the horse’s face. Several pictures of horses, ponies, and foals were used to help determine the ratio to use.

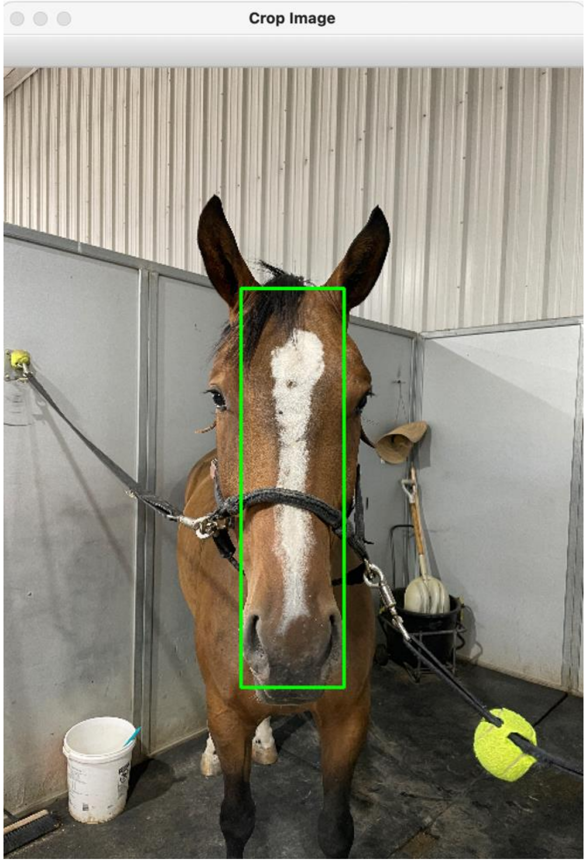
With a classifier that could now successfully detect the region of interest for a horse face using images with horses in ideal positions with ears forward, it needed to be tested on pictures that are more representative of real-life barn situations. It became clear that busy backgrounds, such as corrugated metal, and horses in the distance created problems for the classifier, as can be seen in the following image.



Initial runs, as shown previously, were used on full size, high resolution images. By reducing an image resolution to 1/6th of the original, the classifier greatly reduced false positives on background objects including horses in the distance. The results of using the reduced image size can be seen below.



As the classifier was now successfully detecting the horse faces from the images, some more thought was given to what information would be most useful for recognition. While the ears and overall face shape do contain valuable information there were challenges seen with including them. These included that the ears often move if a horse is listening to their surroundings and are also used by the horse to reflect their mood. The inclusion of the whole face also meant that the images used for training and testing would include much of the background since a horse's head shape does not fit well in a rectangle. This results in a lot of the image containing information that is not valuable for identification. Because of these concerns, it was determined that the center of the horse's head, between the eyes from the forelock to the nose, would be the focus for recognition. General ratios that could be applied to the image based on the ear location still offered reliable results in determining the region of interest. A picture with the updated region of interest is shown below.

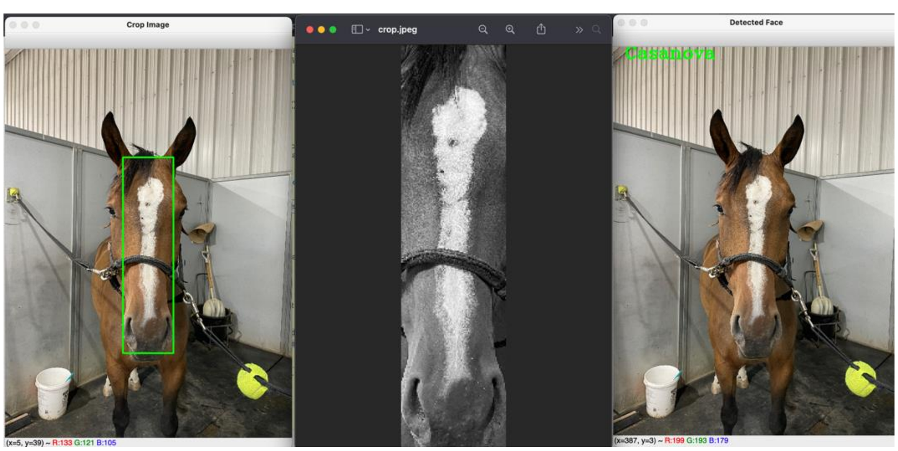


The updates made to parameters in the Haar cascade classifier, as well as adjustments to the image resolution created a classifier that was generally reliable and able to determine the proper region of interest in an image.

Five horses were selected, and several pictures were taken of each to use as a training set. Training sets ranged from 11 to 15 images. The full area of each image was loaded, then cropped to the region of interest. Although the classifier model was performing well, it would on occasion return multiple regions of interest. To handle an image with multiple regions of interest a loop was created where the user could iterate through the multiple regions of interest (if there were multiple) and decide to accept or ignore the proposed regions. Regions that were accepted were saved to the training directory. An example of images used for training can be seen below.

After all images were cropped, a model was trained on the images using Local Binary Pattern Histograms. This method looks at each pixel and the surrounding pixels and creates a histogram to represent them. When performing recognition, it creates the same histogram for the test image and compares to the histograms of the training data. This model was selected because it has proven effective in varying light conditions and with image rotations [4]. Since horses move between indoor and outdoor areas and head rotation is always possible this method was selected.

After training, the equine facial recognition model was ready for use. A Python script was written so that a user is prompted for a file path to a test image. They are then shown the cropped image and can accept or reject and view other regions of interest found. Once a region of interest is selected the OpenCV package is used to create the Local Binary Pattern Histogram described earlier and compare it to the training data and returns the original image with the name of the horse the model determined was in the image. An example of the input image with the proposed region of interest, the cropped image that is used for recognition, and the final output are shown below.

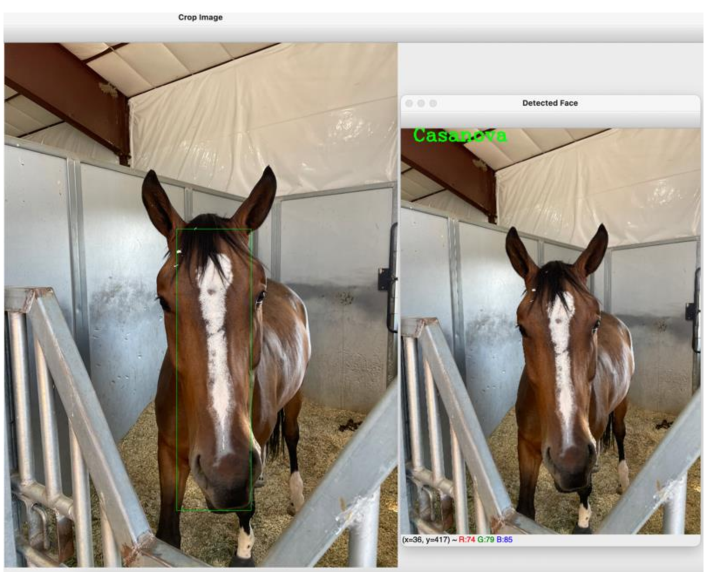


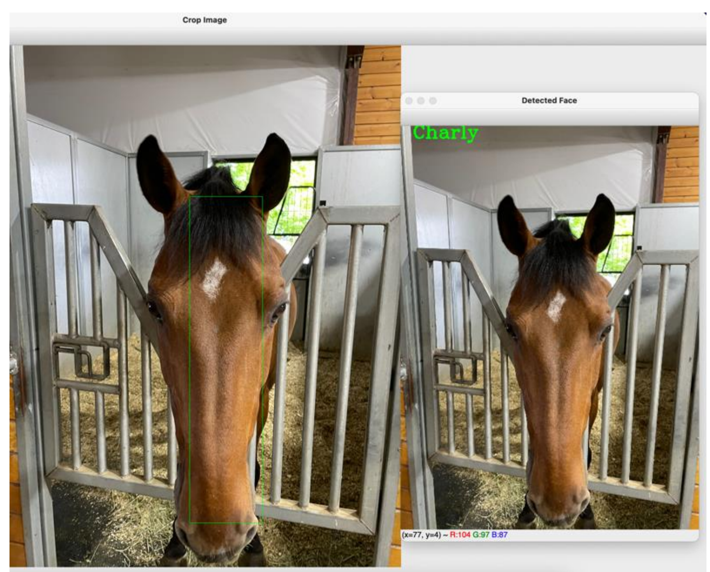
Evaluation and Final Results

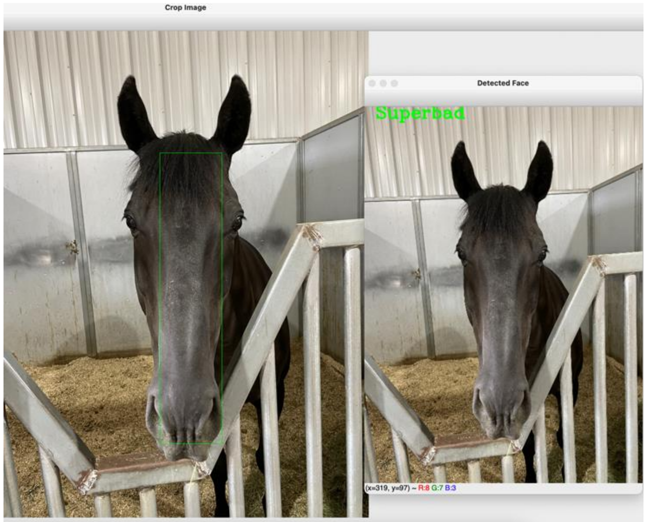
Evaluation was done by taking one new picture of each of the horses in the training set and using the Haar classifier to identify the horse face and crop based on the ratios developed earlier. After cropping the image down to the region of interest, the facial recognition was run to compare the horse in the region of interest to the trained model.

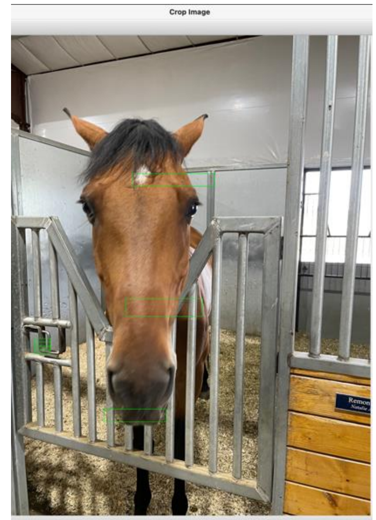
The horses used in training the model are, from left to right, Casanova, Charly, Superbad, Turbo, and Vago.

When doing the first round of testing with image cropping the model was able to correctly identify three of the five horses. In the test images, Turbo's ears were present but the classifier did not detect them, possibly due to background variations behind the ears. In his image, Vago did not have his ears up and so the Haar classifier was not able to locate a face without the ears as a landmark. The results for each horse in the testing data are shown below.

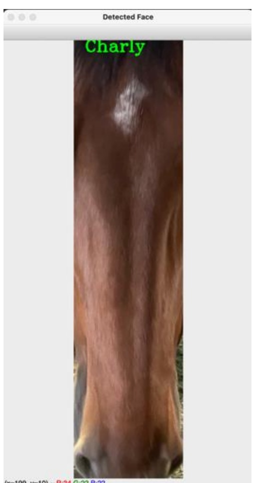


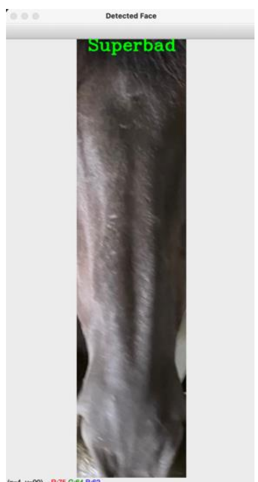


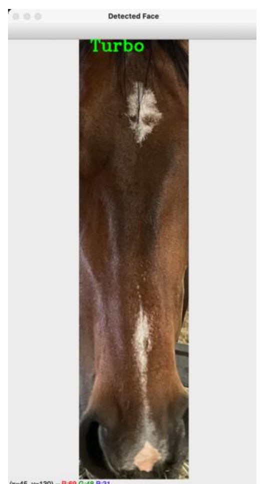


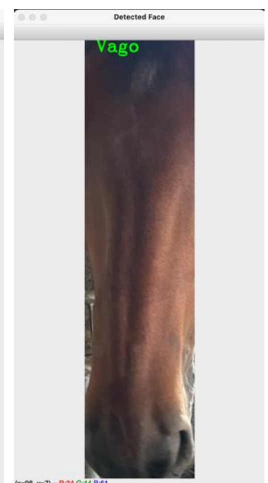


Images were than manually cropped and rotated if needed and the model was able to successfully identify all five horses. The full images that were cropped with the classifier were used first since the end user would not want to take many pictures or crop the image manually, but testing the cropped images was done to confirm performance of the recognition system and prove it capable of differentiating between horses.

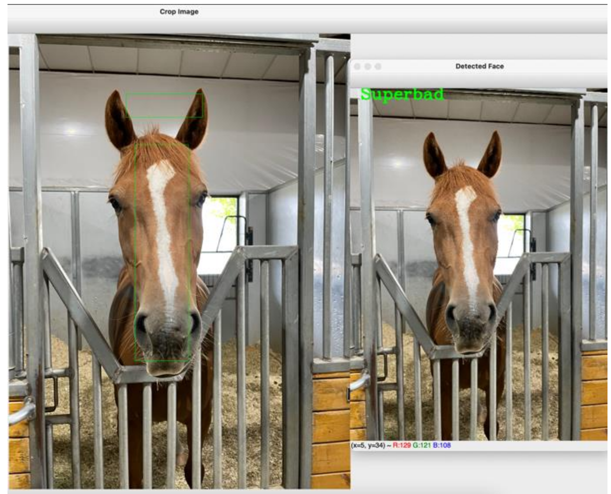








Two additional horses that were not in the training set were also presented for identification. Since the model is setup so that it will always return a result, these were unsurprisingly identified incorrectly.



These results show the model is highly capable of identifying the horses that it was trained to identify, but the biggest room for improvement is in detecting a horse face in the image. A new Haar classifier could be trained that would not rely on the ears to hopefully have a more stable landmark to use for determining the region of interest. In addition, rotation correction could also be added to account for the tilt of the horse's head. Other methods of face detection, such as convolutional neural networks may also be able to perform better than the Haar cascade classifier that was used.

The second shortcoming that was determined from the test data was that the current model will always return a result. Even in a case where there is not a good match it will return the 'closest' match. Finding a threshold for model confidence that could be used to determine if a horse is in the training set or not would help to resolve this issue.

Although not seen in this project, there is the potential for future issues when scaling up the number of horses in a database. Some horses have very similar appearances, such as Charly and Vago from the test data. In the case of the test data, with manual cropping, the model was able to correctly identify both of them. In a large pool of horses, such as at a statewide or national system, differentiation could be challenging. One potential workaround for this issue would be to focus on small subsets of the data. For example, only the horses at one barn, or only the clients of a specific veterinarian.

The overall model results showed that a horse facial recognition system can be created and it can successfully differentiate between multiple horses, even when facial markings are similar. The model did, however, show that there is room for improvement particularly in the area of horse facial detection and preparing the image for facial recognition.

References

1. Nancy S. Loving, DVM (2018). ‘The State of Microchip Use in Horses’, The Horse, https://thehorse.com/19431/the-state-of-the-microchip/

2. Steve North, Carol Hall, Amanda Roshier, and Clara Mancini, 2015. HABIT: Horse Automated Behaviour Identification Tool – A Position Paper. In Proceedings of the proceedings of ACI@BHCI (Animal Computer Interaction Workshop), British HCI 2015 (Lincoln, UK, 13 July 2015), BCS, UK. http://dx.doi.org/10.13140/RG.2.1.3395.0881.

3. Viola, P., & Jones, M. (2001). ‘Rapid Object Detection using a Boosted Cascade of Simple Features’. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

4. Sierra, Brandon Luis, "COMPARING AND IMPROVING FACIAL RECOGNITION METHOD" (2017). Electronic Theses, Projects, and Dissertations. 575. https://scholarworks.lib.csusb.edu/etd/575