Personalized Alert System Analysis

1. Problem Context

This project is intended to build a personalized model which is able to distinguish between a set of situations given an image. In this case the model will be trained on determining if a dog is being taken out or put into its crate, however, this idea can easily be generalized to monitor and alert users for a number of different personalized situations.

Although the model itself would only be capable of classifying these personal situations based upon an image it could easily be integrated into a system which monitors using a video camera and alerts a user based upon different classification readings. For instance, a sequence of situations could trigger an email or text message to a user which could provide valuable real time information making it a useful product for some consumers. The heart of this system would be the classification model engineered in this project.

A system such as this is useful for situations where simple electronic triggers are not applicable or too expensive to be useful in classifying what is going on. Going back to the example used in this project, a dog crate with electronic features is unnecessarily expensive and would arguably still lack the robustness of a machine learning monitoring system. Other useful situations could be monitoring a baby in a crib or monitoring places such as kitchen cabinets or a garage where you want to be alerted of certain people entering. These problems are simple to a human but have no easy automated solutions without the use of machine learning.

To develop the model, the system will use a set of videos representing each situation that needs to be recognized. In this case it will be the dog in the crate, the dog not in the crate, and the dog being taken out of the crate. The videos will be parsed into a set of images which will then be used to train the model. The model will use Deep Neural Networks for this classification process.

2. Data Collection

For generating the data, six separate videos were taken, two for each class in the problem averaging around a minute and a half each. The videos were parsed into JPG files for each frame using the 'Free Video to JPG Converter' application from Microsoft. Then using the Python module 'skimage' the images were iteratively resized, reshaped, classified, and stored into a set of CSV files. The images were also converted from color into grey scale. This was done because color images take up three times the amount of memory and caused performance issues in the project. Each image was rescaled to 8% its original size, again this was tuned for optimizing both image quality and system performance.

After resizing the images, they were flattened into a single dimension, making them convenient for storing as data tables and CSV files. Upon use, these images can be reshaped into their original image dimensions in order to take advantage of local correlations. Videos were taken with only one class occurring through each one, and because of this by knowing the video the image came from classifying each image could be known, allowing automation of the labeling process. Finally, sets of 50 cleaned images were saved to a CSV and given a randomized name. The randomized names of the file help to mix up the classes of data so that the model is not continuously trained on one class for many batches in a row. The data was spread into multiple files due to RAM limitations.

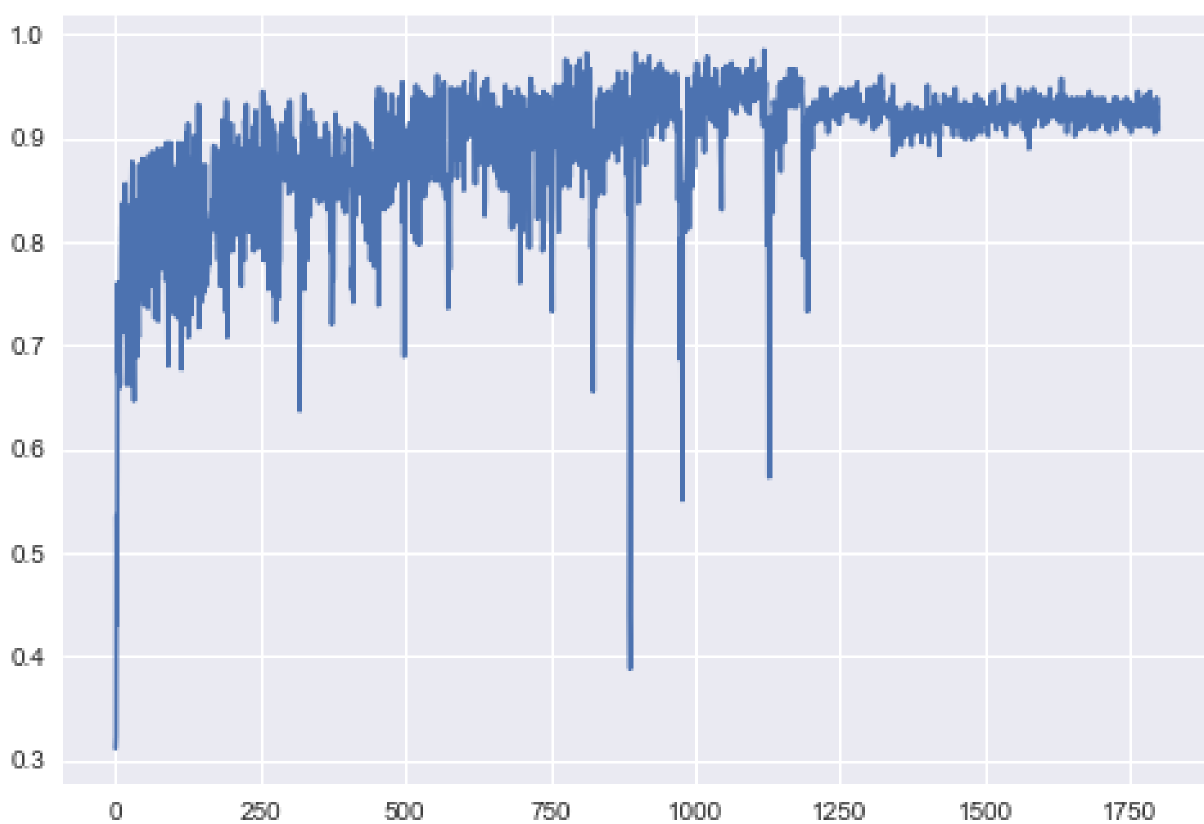
Overall, over 10,000 images were generated each consisting of over 5,000 pixels occupying nearly 7 GB of memory. This created an issue in the project when attempting to push the data to Github. The large size of the files prevented all of the data from moving to the remote repository and because of this data was stored locally with only examples of the images and CSV files stored on the master branch.

3. Benchmark Model

Before using neural network models, a benchmark model was developed for reference using a more standard algorithm. A Random Forest Classifier was chosen because it integrates easily with multiclassification problems. In order to prevent the model from heavily overfitting the data was compressed to 10 features using a Principle Component Analysis algorithm implemented in the Scikit-Learn library. After the resizing the data and fitting to the Random Forest Classifier (also from Scikit-Learn) the model had an impressive 88% accuracy. This could most likely be increased through hyper-parameter tuning and experimenting with the algorithm or data feature size, but a general measure of the performance of more simple models was all that was needed.

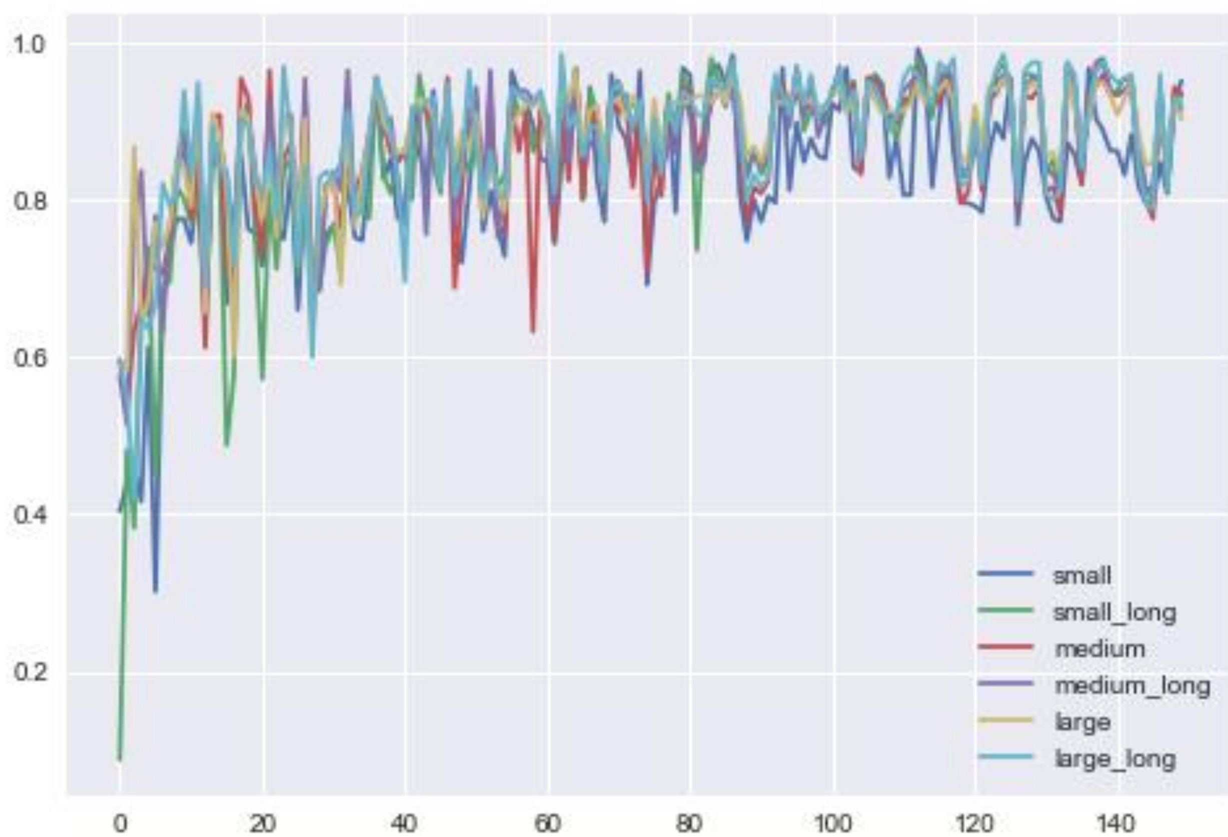
4. Dense Neural Networks

After the benchmark model was created, a simple dense neural network model was generated and fit to the data, using the Keras high level API. This type of network has the most standard architecture where each layer is fully connected to the next layer. At first the following process was used, iterate through each training file and fit the data to the model (meaning a Stochastic Gradient Descent update was made). Every 10 updates test the model on a reserved set of testing data. After each file had been fit on the model an epoch was complete. The first model was trained on 300 epochs and the performance was tracked. The peak performance of the model was over 98% accuracy, far greater than the benchmark model that was created while the mean accuracy of the model after convergence was around 93%. However, the performance was inconsistent over epochs varying as low as 80% accuracy at times.



In order to reduce the noise of the model we randomized the files into larger more integrated sets of data. In the original data collection process entire videos comprised of only one category were parsed in small datasets of very similar images with the same label. The idea was that stochastically updating the model with these uneven datasets could cause the model to overfit and move into a lower performance configuration. To hopefully fix this issue the datasets were aggregated for every 10 small files into 1 larger csv file. By randomly aggregating and shuffling the data each batch fit for the model would have a more even distribution of class labels.

After rearranging the data, a new set of neural network models were created ranging in the size and number of layers. The models were trained over span of 150 epochs in a very similar method as was done with the first neural network model. The models had a peak accuracy just of 99% which was very impressive and a converged mean of about 93% again. Unfortunately, all the models performed relatively equally in the long run and the consistency of the models was not increased by evening the label distributions of the data as suspected.



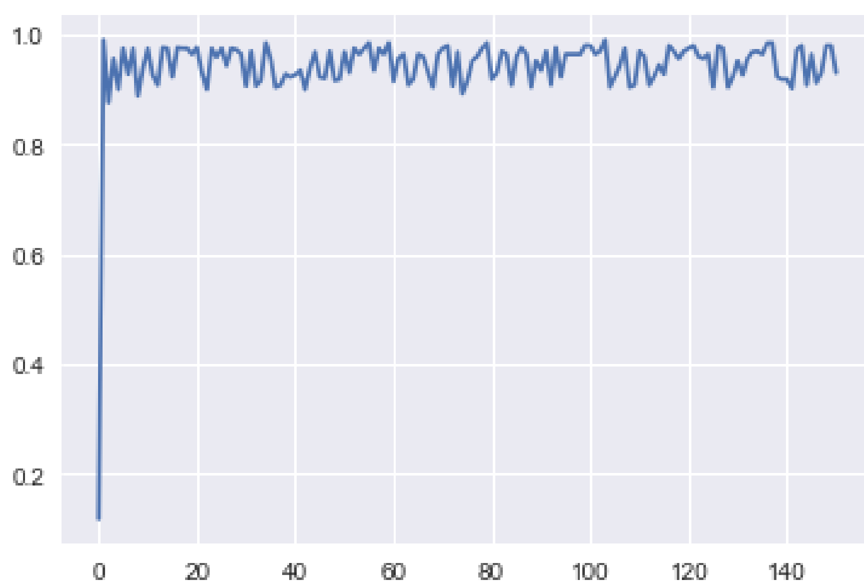
5. Convolutional Neural Network

After experimenting with the more simplistic dense neural networks we began testing with convolutional layers. Convolutional layers use a set of filters, and in this case 2 dimensional ones, which are compared across the entire image. This type of layer allows for the model to search for local patterns which are important in images and time-series data. Unfortunately, this increase the complexity and puts strain on the system training the model and because of this only one small CNN model was trained and still took multiple days to converge. As with the second set of DNNs the model was trained on larger, more diverse csv files over 150 epochs of data.

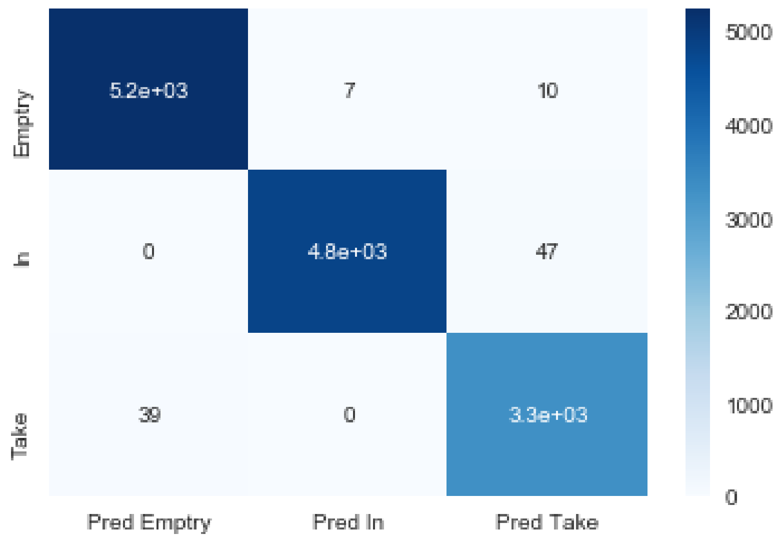
Despite only using one model there were noticeable performance increases. The top training accuracy was again over 99%, but the converged mean accuracy was an improved 95%.

6. Evaluation

As the most successful model the CNN was saved in an h5 format file for later use if needed. The model was then run over all of our data and had a 99.5% accuracy. In looking at the test score throughout training we see that the algorithm both converged faster than the DNNs and had less variance once converged.



By analyzing the confusion matrix, we see some minor weaknesses within the model. Most notably, predicting that the dog is being taken out/put in the crate is the least stable prediction with most of the errors occurring when the dog is in the crate. Predictions for 'in the crate' were the most reliable and Predicting 'empty crate' had all of its misclassification when the dog was being taken out.



7. Improvements

In order to improve the model my first recommendation is to increase the data. By collecting more videos of possibly other dogs the model can be made more robust to outlier situations. Also working with improved resources such as a more powerful computer or even training in an online virtual environment will allow for large models and faster training times increases the ability to experiment with different models. Research in the unbalanced misclassifications displayed in the confusion matrix may also be beneficial.

In this project, only the predictive model was developed. In order to complete the full functionality described, the model needs to be embedded into a system with video capabilities and an online connection. Logic to take pictures, make predictions, and respond accordingly would also need to be developed. Ideally this could be commercialized for situations like baby or dog monitoring. Even allowing the user to take videos of the situations they need and automating the model training online to fit the needs of the user could be a possibility.