Machine Learning as a Validation Tool for Qualitative Difference Analysis

University of Miami—REU Computing for Structure

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Introduction

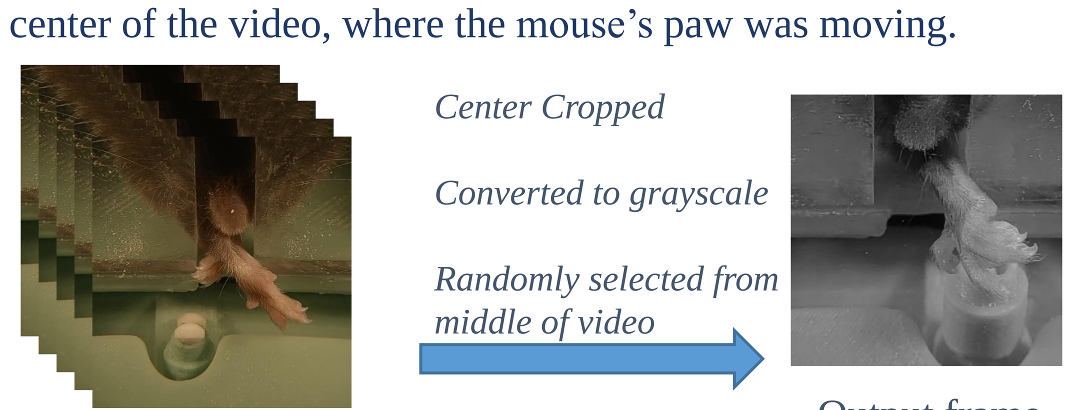
The use of deep learning models to identify differences in data is increasingly popular among researchers. Specifically for visual data, like videos and images which are subjectively evaluated for differences. Machine learning provides the ability to quantify and verify visual differences observed by researchers in addition to finding differences that are not immediately obvious to the human eye.

For this project, machine learning, specifically deep learning, was used in the form of Convolutional Neural Networks (CNNs) to evaluate the difference in movement for mice pre and post injury using binary classification.

The machine learning packages used were Keras, Tensorflow, and Pytorch. Tensorboard was used for model analysis.

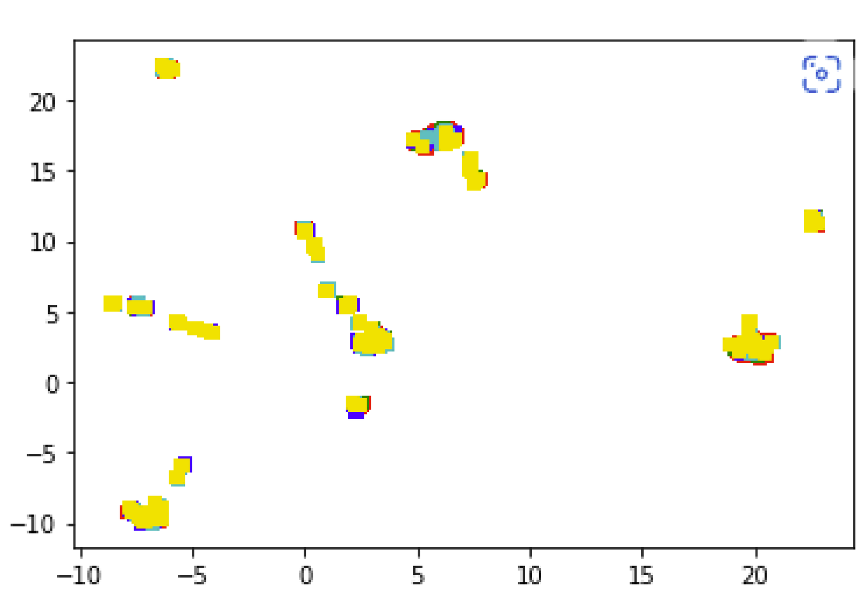
1) Initial Steps

Creating the models began with the processing of the raw video data. Each video was processed into 5 frames randomly selected from the center of the video, where the mouse's paw was moving.



To evaluate the videos of mice pre and post injury, the next step was ensuring that there was a visual difference detectable to a machine learning model. Convolutional Long-Short Term Memory networks are a kind of machine learning that is unsupervised. Unsupervised machine learning, creates categories based on variance in the input data without a human determining these categories. The use of Convolutional Long-Short Term Memory networks and dimension reduction techniques such as PCA, TSNE and UMAP, which reduce the matrix outputs to plottable points, the video input data was able to be plotted and clustered.

UMAP Dimension Reduction Graph



This UMAP plotting of the video input data, indicates distinct categories within the input dataset. It validates the observation that there are differences in the movement of the mice and invites the possibility of successful supervised classification.

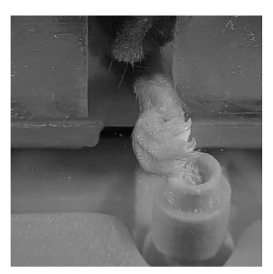
2) Approach

Two datasets were created. For Set One, the data was manually sorted into training and testing data sets. For Set Two, the data was unsorted allowing the computer to select a validation set. For both datasets, the frames were loaded into an array along with labels of 1 for Post-Injury or 0 for Pre-Injury and the data was shuffled to allow the model to train fairly.

Post-Injury Label:

1 

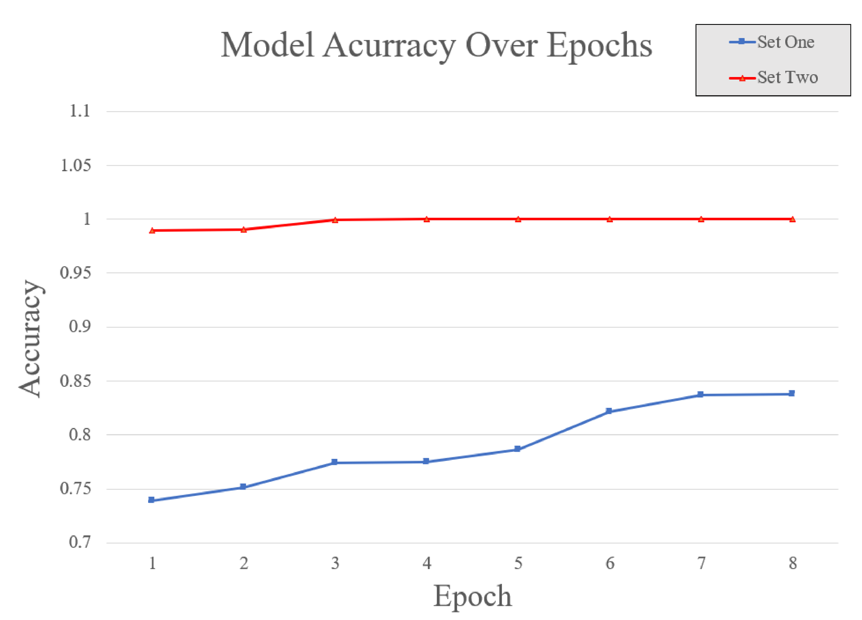
Pre-Injury Label:

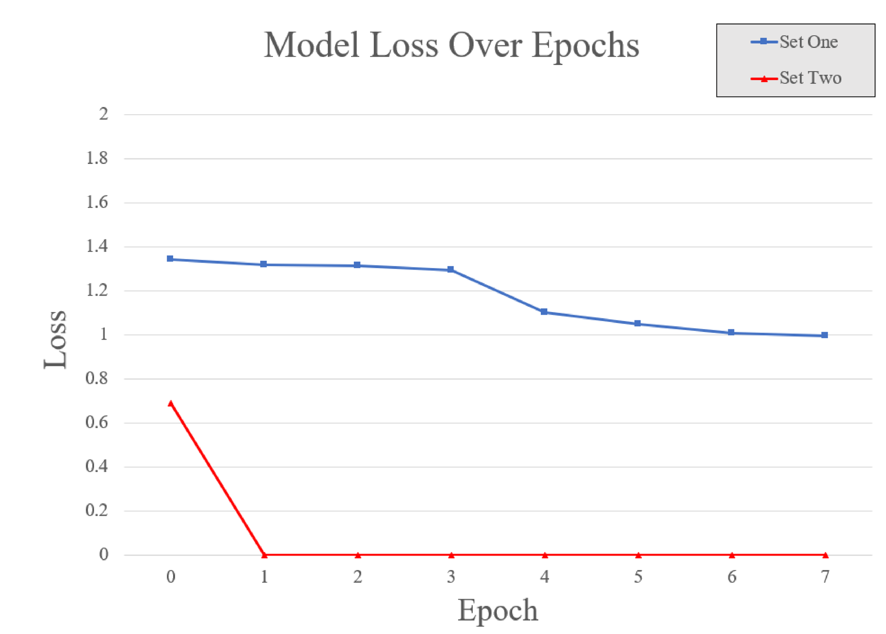
0 

For Set Two, the model returned 100% accuracy, indicating a background factor was skewing the results.

Set One included videos from six mice in both the training and testing sets. This sorting ensured that the model was being tested on animals different from the ones it trained on, which helped to minimize the impact of background factors like lighting, dust, and angle variance on the model.

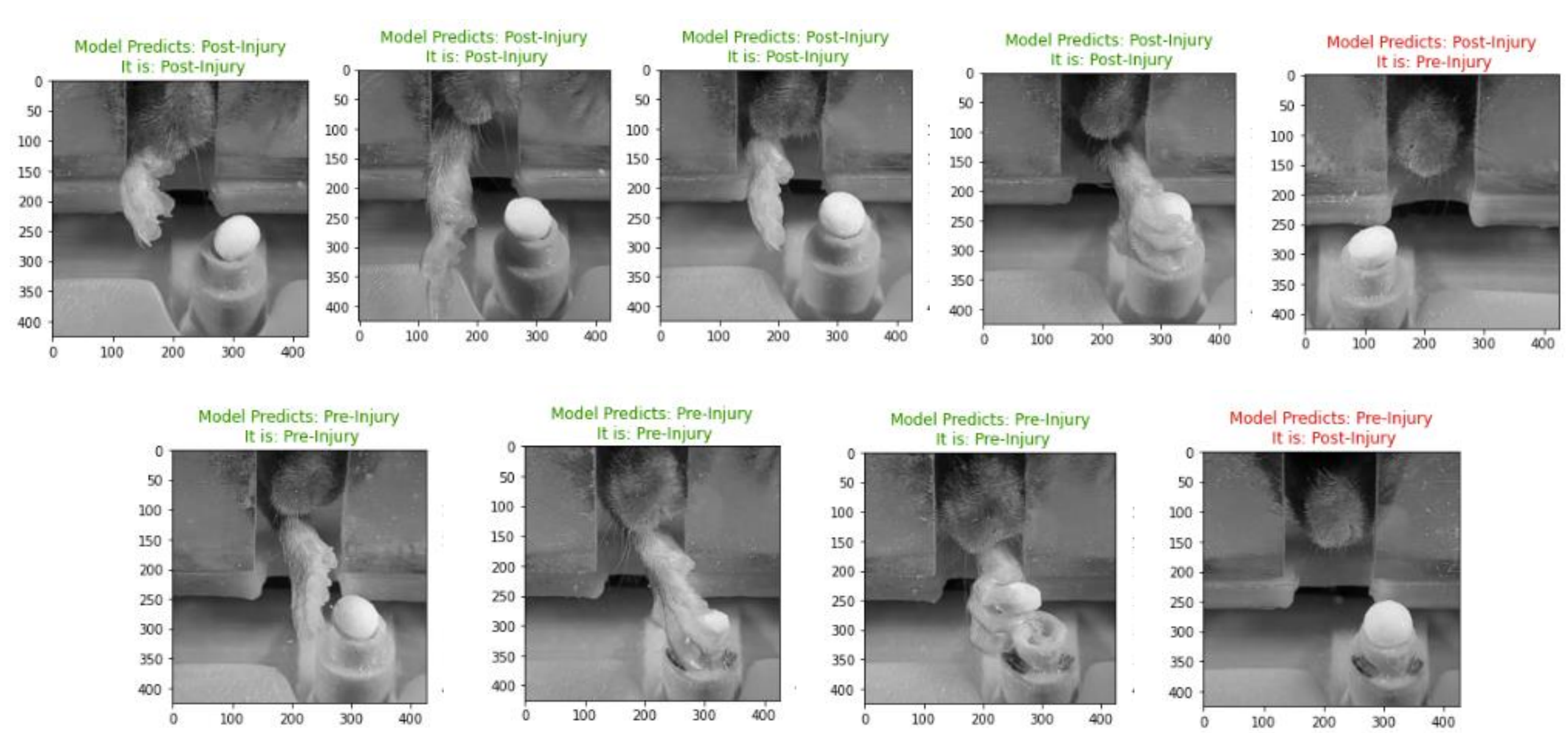
Examples testing the model produced with Set One are pictured in panel 3





3) Results

The main result of this project was the production of a functional model that classifies the difference in movement between pre and post injury mice. The model test accuracy ranges from 75-85%, with many of the incorrectly classified images being ones without the mouse's movement present.

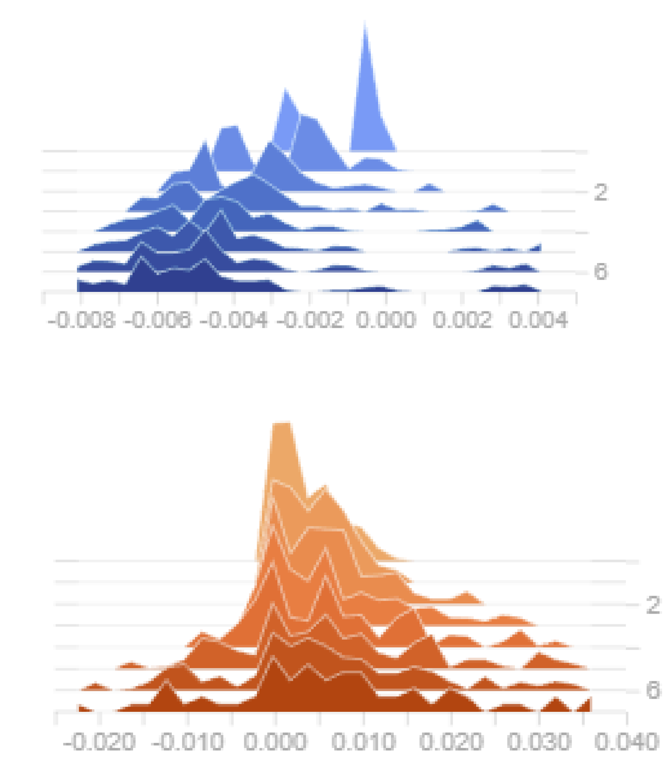


The images above demonstrate how the model is able to detect the different motion in pre and post injury mice. Pre-injury movement is more of a grab with pronation, while post injury resembles a scooping motion.

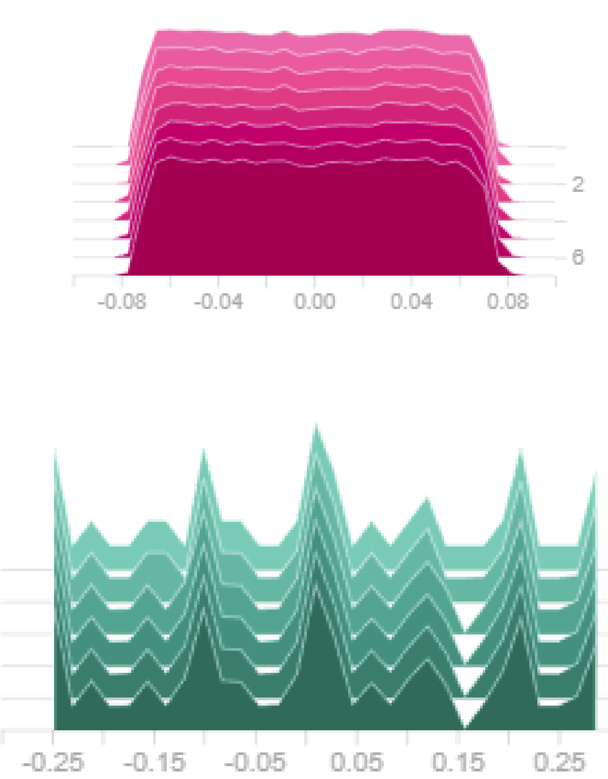
Convolutional Neural Networks

Convolutional neural networks are used in deep-learning for the processing of visual data because of their ability to maintain the spatial relationship of the data. They use a series of filters or kernels with weights to process and reduce the dimensions of an array of image data. CNNs use a bias to represent the difference between the predicted and expected value. They can have many layers depending on how large the dataset is and how complex the feature extraction is. A technique called back-propagation is used to change the weights of the filters to improve the predictions. There are different ways to optimize this. For this model, the optimizer used was "adam", an optimizer that changes the learning rate based on the model improvements.

Bias Value Distribution Graphs



Kernel Weight Distribution Graphs



The graphs above show the bias value for two layers of the CNN. Bias is a measure of the difference between the predicted and expected value, so as the model trains, the bias lowers, indicating a more accurate model.

The graphs above show the kernel/filter weight distribution for two layers in the CNN. The pink graph is the first convolutional layer, which should have a normal weight distribution. The second is the last convolutional layer. The peaks on this indicate that there are points of interest.

4) Conclusions

The ability of the deep learning model to identify differences between pre and post-injury images indicates movements after injury are different from pre-injury even though the mice can still successfully pick up the pellet .

Machine learning can be used to identify differences in visual data in an unbiased and consistent fashion.

Currently machine learning models require a large amount of data processing but provide support for qualitative conclusions.

This model reduces the labor, time, and skill intensive work of manually performing functional analysis on mice.

Acknowledgements

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