Iowa Initiative for Artificial Intelligence

Final Report

Project title:	Machine Learning to Enhance Detection of Depression-Related Behaviors and Improve Throughput in Animal Behavior Assays	
Principal Investigator:	Aislinn Williams, MD, PhD	
Prepared by (IIAI):	Kyungmoo Lee	
Other investigators:	None	
Date:	11/11/22	
Were specific aims fulfilled:	Yes	
Readiness for extramural proposal?	Not yet	
If yes … Planned submission date		
Funding agency		
Grant mechanism		
If no … Why not? What went wrong?	We need to apply this method to new data (we already published the raw data used for this project) but once we successfully do that, we plan to use this for an NIH R01 (or equivalent) grant next year.	

Brief summary of accomplished results:

We have developed a deep learning-based method to automatically predict mouse swimming from video-sequences. Our neural network consists of 3 convolutional layers and 3 dense layers, and 7-fold cross validation with 42 datasets was performed to test the network. The mean area under the curve (AUC) value is 0.899 ± 0.029, and the accuracy between ground truth and our prediction is 0.867.

Research report:

Aims (provided by PI):

The overall objective of this study is to determine how L-type voltage-gated calcium channels influence active versus passive stress coping behaviors.

Aim 1: Use machine learning to predict behavior in the forced swim test.
Aim 2: Determine if behavioral patterns in the forced swim test can predict animal genotype.

Data:

Twenty-one movie files (MOV, frame width: 1280 pixels, frame height: 720 pixels, no. of frames: 6291.9 ± 361.6, frame rate: 19.7 ± 1.0 frames/second) were used for this study, and each movie includes 2 mice swimming or floating. The movies were downsampled by 10 frames/second, converted from color to grayscale, and cropped to create 2 volumes (image x time) of interest (VOIs) (Fig. 1). For analysis, the last 4 minutes of the movies were used since most mice are very active at the beginning of the FST. The ground truth of mouse swimming/floating was created by an expert who recorded the start times of mouse swimming and floating. The time record was converted to 1 for swimming or 0 for floating for each frame of the VOI.

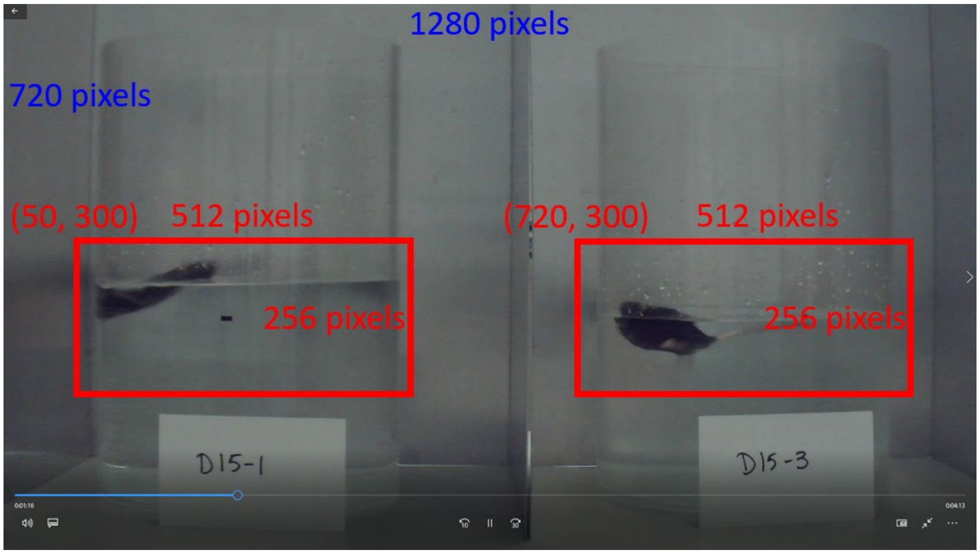

Figure 1: Two volumes of interest (VOIs, red rectangles) cropped from the movie.

AI/ML Approach:

For binary classification of mouse swimming, we designed a neural network consisting of 3 convolutional layers and 3 dense layers [1] (Fig. 2). Nine consecutive frames, down-sampled to 64 x 32 pixels, of the VOI were used as an input for the neural network which was trained using the following hyperparameters.

- Optimizer: root mean squared propagation
- Loss: binary cross-entropy
- Maximum number of epochs: 50

The output of the neural network is a probability between 0 and 1, and the number closer to 1 represents more likely to swimming. The threshold where true positive rate - (1 - false positive rate) is the closest to 0 was used to binarize the probability. Finally, the binarized probability was smoothed using a median filter with the kernel size of 43. Various kernel sizes were tested, and the kernel size of 43 provides the highest prediction accuracy (Fig. 3). Fig.4 shows an example of the thresholded probabilities before/after median filtering.

Experimental methods, validation approach:

To validate our proposed method, 7-fold cross validation was performed with a training dataset of 36 VOIs and a validation dataset of 6 VOIs. The prediction performance was estimated by receiver operating characteristic (ROC) curves and the accuracy between the ground truth and our prediction with the threshold where true positive rate - (1 - false positive rate) is the closest to 0. Additionally, the regression plot of %-time swimming between the ground truth and our prediction was used for validation.

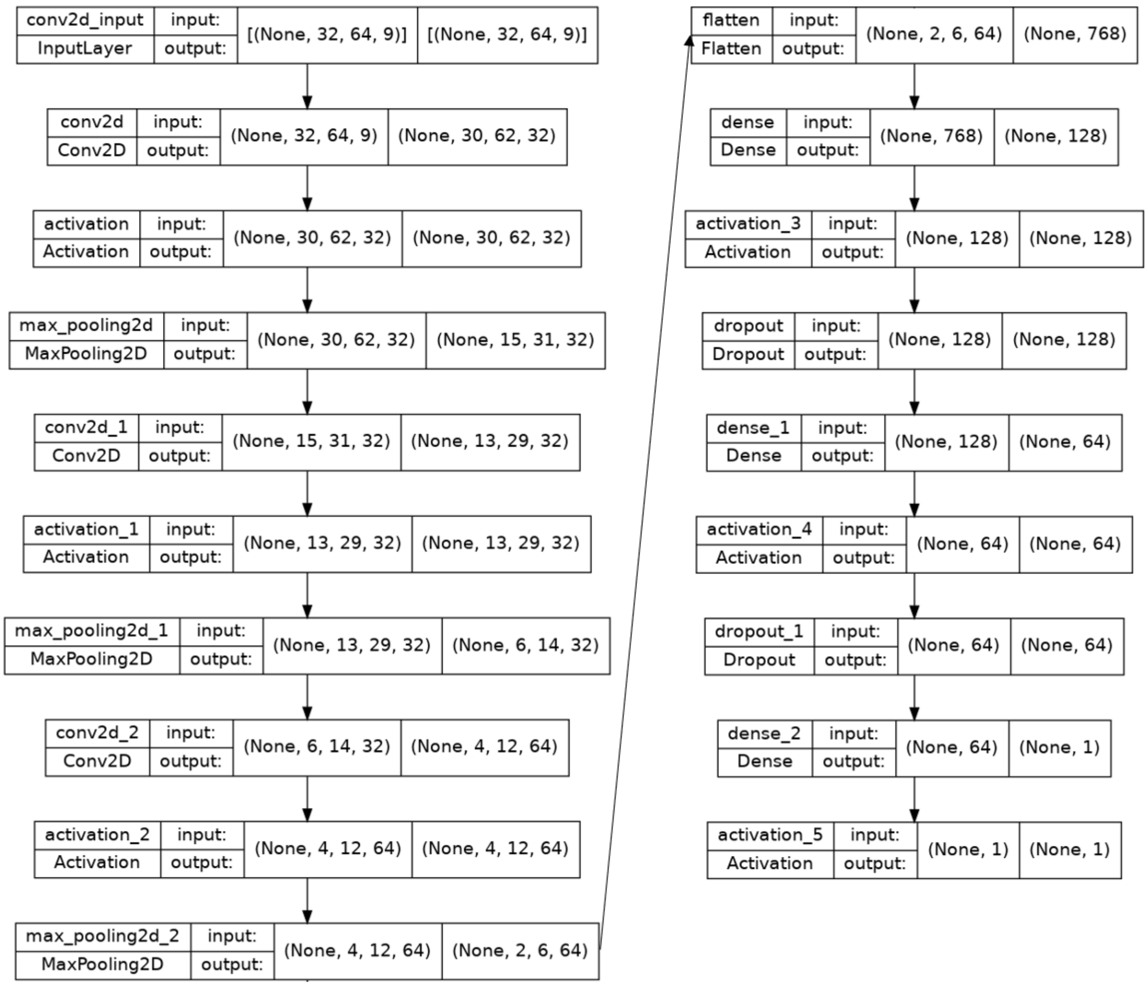

Figure 2. Our neural network for binary classification of mouse swimming.

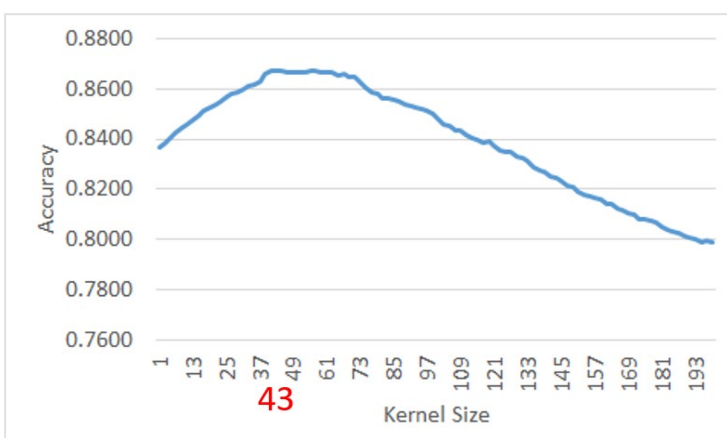

Figure 3. A graph between the kernel size of a median filter and prediction accuracy.

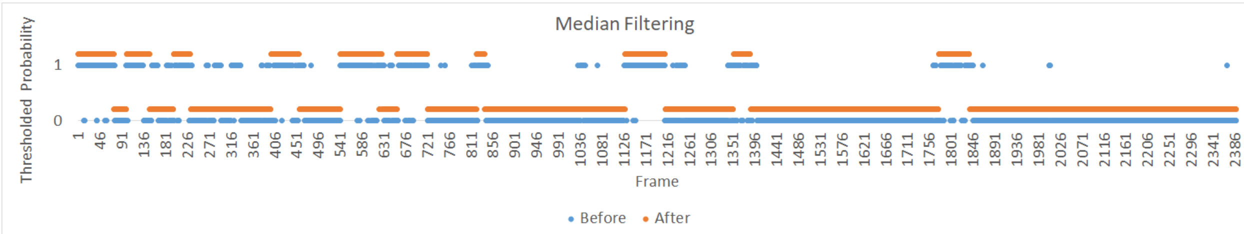

Figure 4. An example of the thresholded probabilities over frame before (blue) and after (orange) median filtering.

Results:

Fig. 5 shows receiver operating characteristic (ROC) curves with AUC values for 7 folds, and the mean AUC value is 0.899 ± 0.029. The accuracy between the ground truth and our prediction is 0.867. Fig. 6 shows the regression plot of %-time swimming between the ground truth and our prediction, and the R^2 value is 0.897.

Fig. 7 shows a typical example of our prediction for individual mouse swimming. All 42 graphs are in a separate Excel file. Fig. 8 shows how to display the ground truth and our prediction on the frame. All 42 AVI and NII.GZ files are in lss_williamsa/Mouse Swimming.

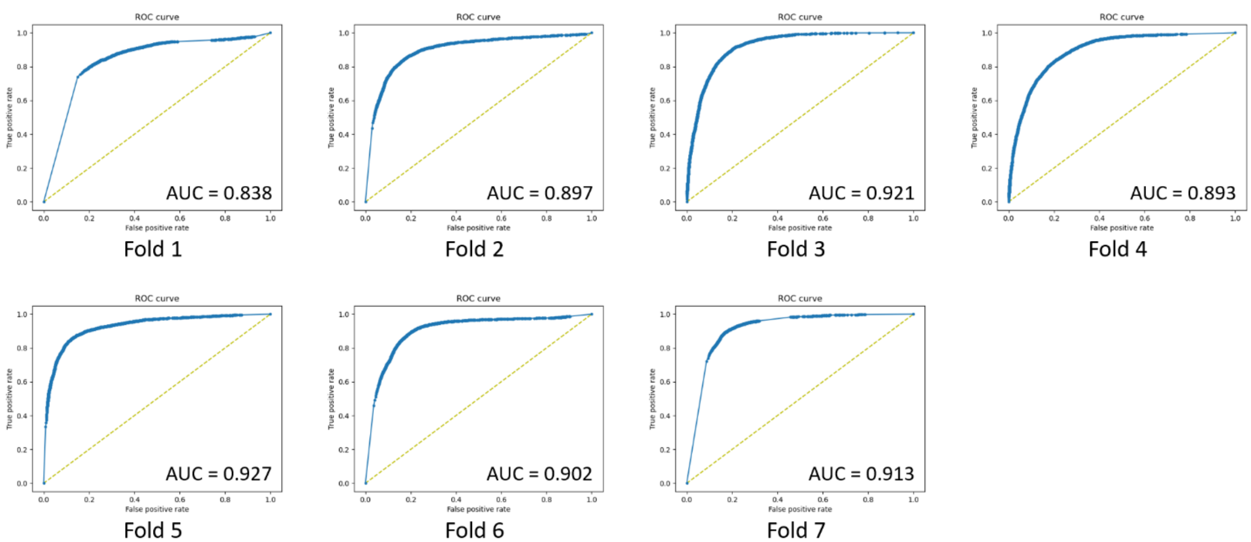

Figure 5. Receiver operating characteristic (ROC) curves with area under the curve (AUC) values for 7 folds.

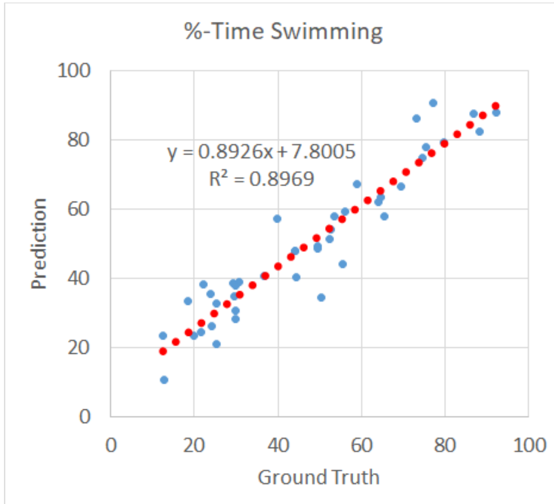

Figure 6. The regression plot of %-time swimming between the ground truth and our prediction.

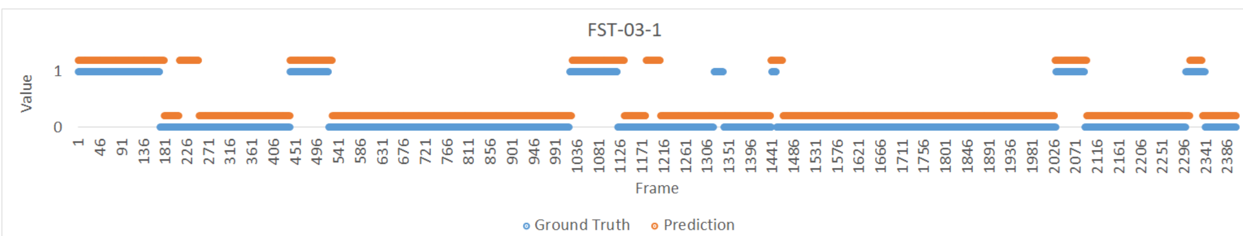

Figure 7. A typical example showing the ground truth (blue) and our prediction (orange) over frame for an individual mouse (1 for swimming, 0 for floating).

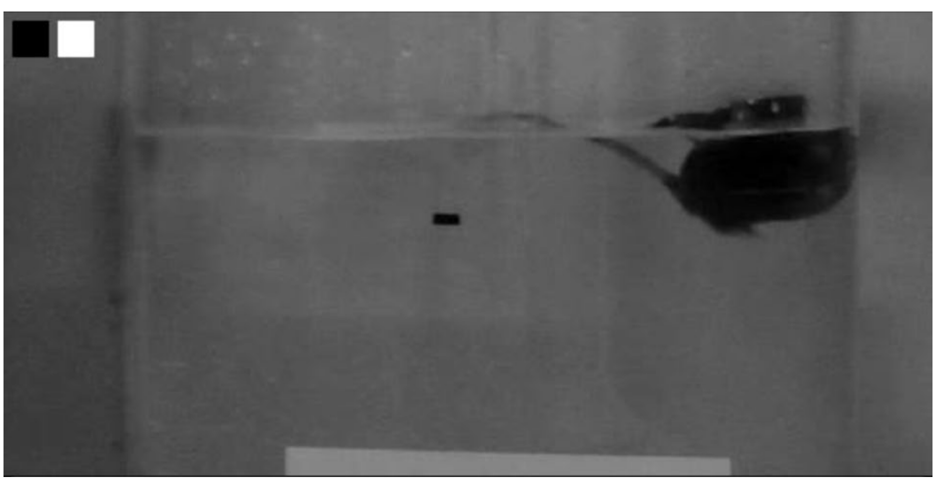

Figure 8. A frame of the VOI showing the ground truth (left square at the upper left corner) and our prediction (right square) (white for swimming, black for floating).

Ideas/aims for future extramural project:

More reliable prediction of mouse swimming would be possible by including more movies taken at various angles. In addition to identification of swimming, swimming speed might be a useful behavioral metric.

Publications resulting from project:

None.

References:

1. Yamashita R, Nishio M, Do RKG, Togashi K. Convolutional neural networks: an overview and application in radiology. Insights Imaging. 2018 Aug;9(4):611-629.