Smart Dog Harness For Seizure Detection

Marji Symonds

Introduction

Epilepsy affects 1 out every 130 dogs (0.75%), a condition that affects both the well-being of the canine and owner. Current standard methods for monitoring epilepsy are often invasive for patients, as they use a combination of video and EEG to capture critical data points. However, non-invasive reporting of seizure episodes in dogs will allow clinicians to fully track a patient's seizure history and thus better inform the treatment of their epileptic patients. This project focuses on using accelerometric and gyroscopic sensors to detect and identify movement in order to capture critical data points in canine epilepsy.

Background

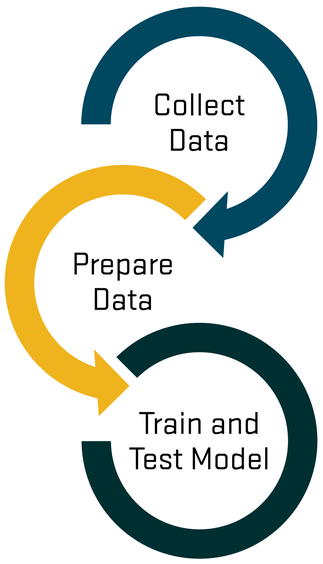
The prototype is a wifi-enabled microcontroller equipped with accelerometer and gyroscope sensors. The prototype is powered by a portable battery and placed in a pouch strapped around the dog's midsection. Using this model, movement data is recorded at 20Hz and transmitted via wifi to cloud storage. Movement data for each of the six defined types of activity was gathered and tracked to use for the machine learning experiment.

Dataset

To prepare our device to detect seizures, we trained our machine learning model with six general canine movement patterns with the goal of identifying the movement type in a small length of activity data. Each data collecting session was focused in one of the six categories:

Sleep · Walk · Leisure · Run/Jog · Car Ride

Methods & Results



We collected 423,623 seconds of movement data from three dog subjects over four months. We conducted preliminary experiments using different sequence lengths and hop sizes to find the optimal balance of accuracy and responsiveness. We found a four second sequence length with no overlap to be ideal for use with a 2D convolutional neural network (2-CNN) model.

In Experiment one, we tested the difference in balanced and unbalanced activity data. Due to the nature of seizures, we have much fewer readings compared to our activities, so seizures were not included in the balanced dataset. We used 15,850 seconds of data from each activity in the balanced dataset. We found that the model performed better when given the balanced dataset with an average prediction accuracy of 89.9%. We comprised the unbalanced dataset with a range of 9,820 seconds to 166,290 seconds of activity. We found an average of 82.1% accuracy for the unbalanced dataset. Despite the lower overall accuracy, the model was able to identify seizures with 97% accuracy.

In Experiment two, we cross-validated with data separated by each dog. Once separated, we trained the model with data from two dogs and tested with data from the third. This process was repeated for each dog and we found an average prediction accuracy of 80.7%.

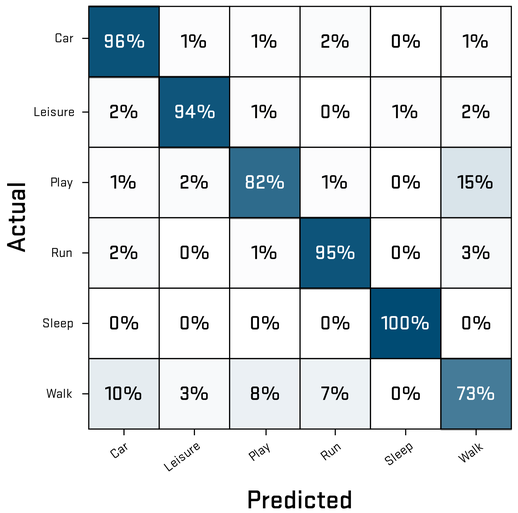


Figure 1: Accuracy of balanced data

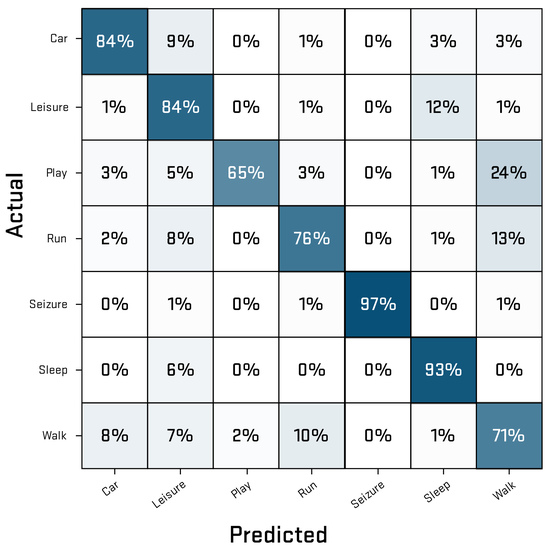


Figure 2: Accuracy of unbalanced data

Discussion

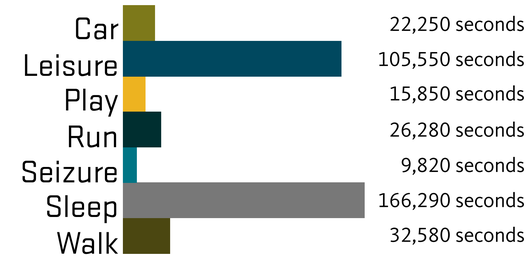


Figure 3: Ratio of readings by activity

Although our data is limited, our results are very promising. Despite reduced accuracy for unbalanced data, seizure identification showed the strongest accuracy. This indicates that the distinct nature of seizure movement may make it easier to detect.

When experimenting with our balanced dataset, Sleep had the highest rate of correct identification with 100% accuracy. Walk had the lowest rate of correct identification, most often being confused for Play, with 73% accuracy. This misidentification was expected, as Play for some subjects is not very active, and tends to involve walking around and exploring.

While slightly less accurate than other experiments, cross-validation does help to strengthen confidence that the results will be generalizable, and our methods will be effective in a future study with more dogs.

Conclusion

Our method of movement analysis provides a non-invasive way to reliably identify canine movements. We were able to correctly categorize movement types and identify seizures.

We plan to continue improving our prototype to allow for easier set up via Bluetooth. Additionally, we are currently developing a web app for easy activity tracking. Our future work will focus on a large-scale trial in conjunction with veterinarians to identify epileptic subjects for further research.

Abstract

We propose a wifi-enabled dog harness for the collection of data of seizure episodes in canines. In this work, we present a system that combines a microcontroller, an array of non-invasive sensors, and machine learning algorithms to analyze sensor data from various movement patterns in canines. The development of this device will support the collection of data from epileptic dogs in future clinical trials.

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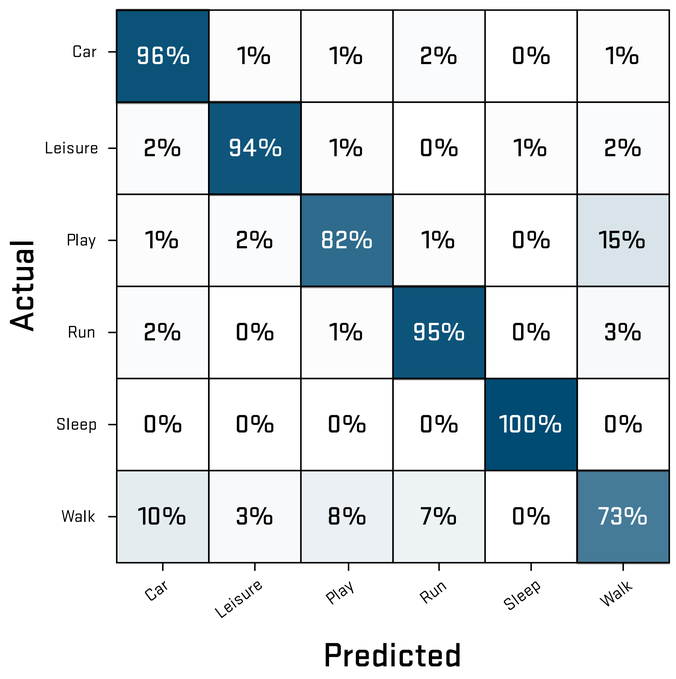
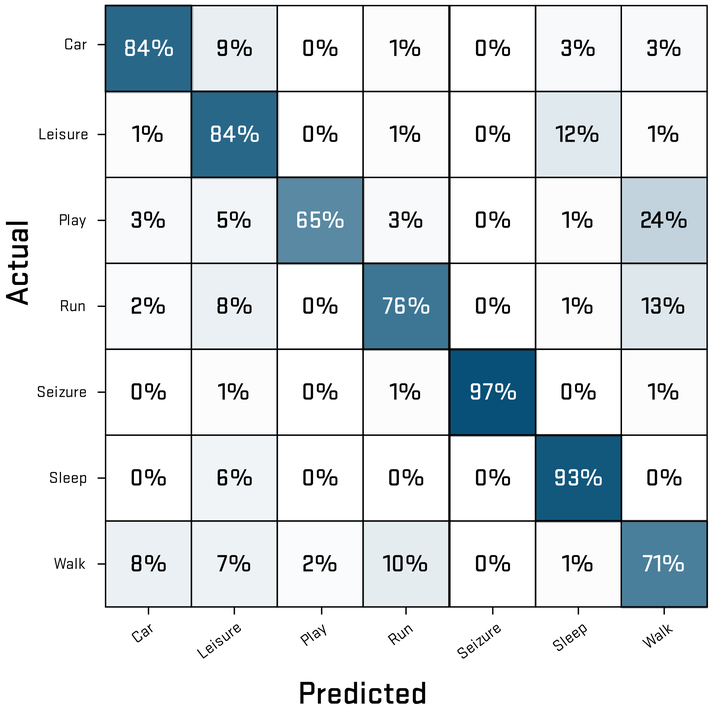


Figure 1: Accuracy of balanced data



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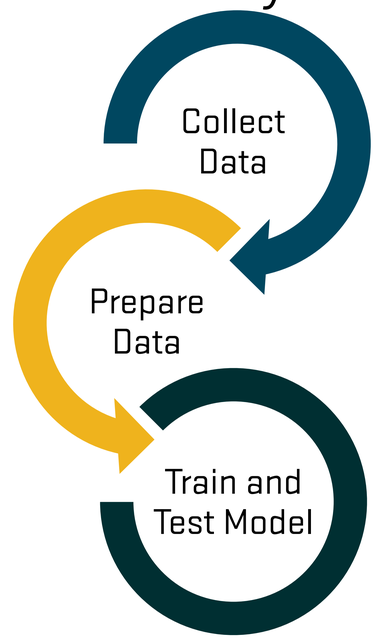

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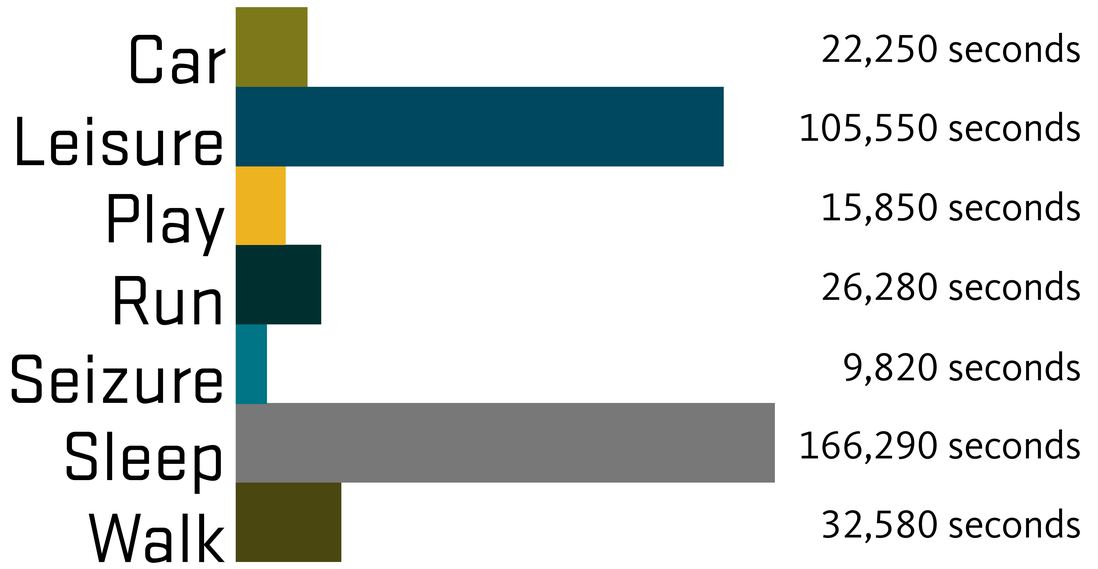

Figure 3: Ratio of readings by activity

Conclusion

Movement analysis through sensors provides a non-invasive way to reliably identify canine movements. We were able to correctly categorize movement types, and early data indicates we will be able to apply these techniques to identify seizures.

We plan to continue improving our prototype to allow for easier set up via Bluetooth. Additionally, we are currently developing a web application for easy activity tracking. Our future work will focus on a large-scale trial in conjunction with veterinarians to identify epileptic subjects for further research.