Smart Wildlife Sentinel (SWS): Preventing Wildlife-Vehicle Collisions and Monitoring Road Ecology with Embedded IoT Systems and Machine Learning

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***Abstract*— Every year in the US, millions of animals are hit by vehicles, making wildlife vehicle collisions (WVCs) a real danger to both animal and human life. In addition, road networks are abiotic barriers to wildlife migration between regions, creating ripple effects on ecosystems. In this paper, a smart wildlife sentinel sign system is demonstrated, utilizing the technologies of Internet of Things (IoT), image recognition, data processing and visualization. This smart system is intended to prevent WVCs by warning driver early once sensors are triggered. Simultaneously, animal images are captured via infrared camera. Data processing and collection are conducted through computer vision filtering, convolutional neural network (CNN) based image classification, and animal activity metadata generation. Wildlife activity data can be exported wirelessly to cloud databases to assist ecologists and government road agencies to further analyze wildlife activity hotspots and potential migration patterns over time.**

Keywords—Wildlife Vehicle Collision, Road Ecology, IoT, Machine Learning, Convolutional Neural Network, Computer Vision

I. Introduction

Along America's highways, roads cross through the habitat of many native wildlife species. When road networks clash with animal movement, WVCs can occur. This presents a real danger to human safety as well as wildlife survival. According to crash statistics data of the Oregon Department of Transportation (ODOT), there were about 1,250 large animal involved wildlife vehicle collisions reported in the state of Oregon in 2014 [1]. Nationwide, estimates quote up to 2 million WVCs annually. Consequently, over 200 human deaths and 26,000 critical human injury hospitalizations are recorded. Insurance claims further report over 8 billion USD lost in property damage and collision related costs per year [2]. Beyond the direct implications, roads represent abiotic barriers to wildlife migration due to a lack of traversability. Overall, WVCs are a serious problem that hurts animal populations, risks human life, and harms infrastructure.

According to Department of Transportation studies, early driver warnings can significantly reduce accident severity and frequency. Warning mechanisms provide a significant margin of over 0.8 seconds reaction time and 21 meters of stopping distance for drivers to react in dynamic road and weather situations [2]. Thus, early driver warning systems are critical to preventing WVCs.

Of currently applied solutions, there are a variety of limitations with traditional warning signage, such as poor visibility during night and bad weather, short reaction time for drivers and a lack of ability in providing insight on wildlife behavior dynamically. These passive solutions are also unable to effectively prevent WVCs. Furthermore, infrastructure built to help mitigate collisions via wildlife path assistance such as animal overpasses, underpasses, and wire-fencing can be expensive and ineffectual if the construction is based on inadequate or outdated information. Current wildlife activity data used for these solutions is collected from human sightings or radio collars, with potential miscount error. Limited timely wildlife activity data represents a black box as recent wildlife-vehicle conflict data is a clear marker for future WVC. Thus, an innovative IoT and machine learning based smart wildlife sentinel (SWS) system is designed to achieve the key functional goals:

1) *Provide early warning signal to drivers of animal presence through flashing LED light matrix as soon as sensors are triggered*
2) *Dynamically take animal images, record metadata, and transmit data wirelessly, which involves:*
    a. Wildlife species classifcation through image processing and machine learning; categorize animal activity based on different species types
    b. Live collected data to be wirelessly transmitted via Ad-Hoc network
3) *Use received wildlife activity data to generate seasonal animal activity maps, identify activity hot spots, and help predict migration patterns over time for wildlife populations*

II. Approaches and Implementation

The SWS hardware system involves an infrared and microwave radar sensor array, LED light matrix, No-InfraRed (NoIR) camera, Raspberry Pi, Ad-Hoc WiFi transmission module, and solar offline power generator. An IoT based, energy efficient, low-cost, and compact prototype is built and shown in Figure 1. In the function of wildlife detection, this self-sustaining smart system utilizes two passive infrared sensor alongside a microwave radar sensor to provide consistent and accurate detection of animal presence. This combination of infrared and radar can detect both changes in heat signature and depth respectively within the ambient environment, thus mitigating possible false triggers of the warning system.

Once the sensor array detects an animal presence in the environment, it triggers a warning signal from the LED light Matrix. Facing incoming traffic, the flickering lights indicate to drivers to slow down in preparation for animal activity. At the same time, the NoIR camera facing opposite the road can simultaneously snap a picture of the surrounding environment. This saved environment image is directly imported to an onboard pre-trained machine learning model loaded onto the Raspberry Pi via TensorFlow Lite for live classification, if any, of the wildlife species captured. The SWS packages all these components together in a compact and modular design allowing for flexible configuration depending on field conditions.

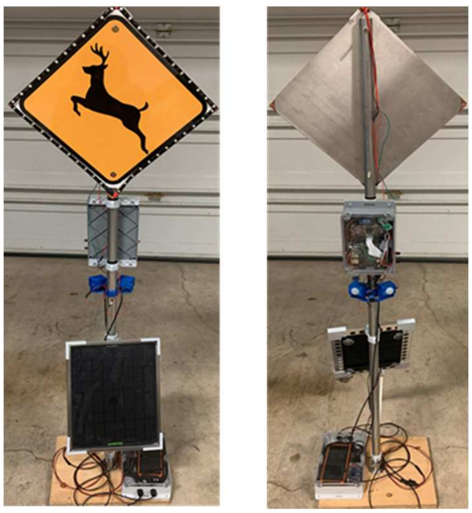

Fig. 1. Prototype Pictured from Front side (left) and Back side (Right)

The identified wildlife species as well as metadata such as location and time are organized together, which is then saved into a data log file ready for exporting. This log file is to be sent via Ad-Hoc WiFi to a remote server for further analysis such as hotspot mapping. With deep insight on wildlife species, geographic location, time, and species, seasonal bubble choropleth maps of wildlife activity can be pieced together. The entire data collection process can be seen in Figure 2. After a collection period, the warning sign is intended to offload data via an ad-hoc WiFi direct transmission for app pickup of the wildlife activity database.

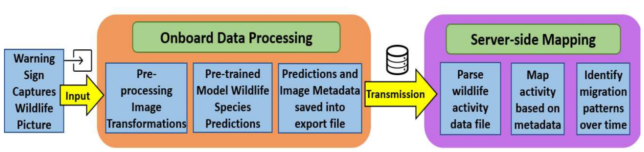

Fig. 2. Warning Sign Data Collection Architecture

In this project, VGG16 deep Convolutional Neural Network (CNN) is used to optimize training efficiency of wildlife species classification in terms of training times and accuracy [3]. The training study is conducted through the US Department of Fish and Wildlife (USDFW) Image library using Python-based TensorFlow and Keras. Over 5000 images of 6 different wildlife species are used for model training based on the frequency of which they appear in roadkill collisions: black-tailed deer, mule deer, rocky mountain elk, Roosevelt elk, coyote, and cougar. These images are then randomly shuffled and distributed into sets for training/validation in an 70%-20%-10% blend.

Besides a baseline model with no image processing techniques applied, different image filters and blurs techniques such as the Gaussian Blur, Median filter [4] and Laplacian filter were tested in application to the CNN and compared to improve the accuracy and training efficiency of the model [5]. Each of the methods implements unique modifications to the image via background blending, overall noise reduction, and gradients respectively.

III. Experimental Results

To evaluate the SWS before real deployment alongside roads, the prototype was first tested at the Tualatin River National Wildlife Refuge across 3 week periods between January and April 2022 to test the key functional goals (Fig. 3).

A. *Hardware Robustness*

Fig. 3. SWS Deployment in the Wild

Outdoor and remote deployment requires a fully autonomous system that is self-sufficient in terms of reliability and energy efficiency. During the deployment period, the SWS was evaluated for ability to achieve prescribed system functions relative to hardware power constraints. Each hour, the SWS would save to file an update on battery power levels as well as a quick check that all system processes were still actively running. During each three week deployment, the SWS maintained functional system activity consistently above 80% each day and was always at a minimum 50% battery charge per day. This dip in power may be attributed to differing solar power generation because of seasonal weather.

B. *Sensor and Camera*

Before starting up the system, the sensor array undergoes a 30 second warm up where it fires infrared beams back and forth. Camera calibration is conducted over a 5 second period where the camera is awoken and focuses to a tuned distance of 15 meters at a quality of 1080p.

Sensor ranges show about 5 meters of detection difference in maximum detection range due to daytime and night-time temperature variation (Fig. 4). The sensor calibration also tested with stable detection range when objects pass at different velocities across these daytime and night-time situations. Regardless of the animal travel velocity, sensor ranges remained

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consistent with changes only occurring due to temperature variance (Fig. 5). Wireless ad-hoc transmission distance is also tested in a flat open field for ping duration during file transmission from transmitter to receiver, which is then converted to distance. From tests, an average transmission range is about 225 meters (Fig. 6). This significant range presents strong potential for remote deployments, where communication signal may be distanced.

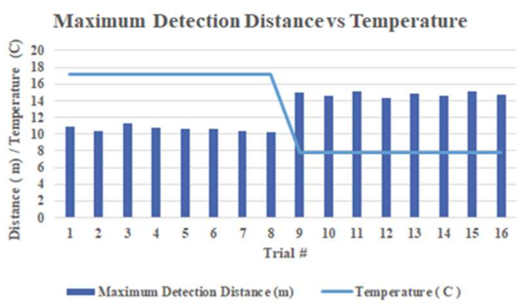

Fig. 4. Maximum Sensor Detection Range vs. Ambient Temperature

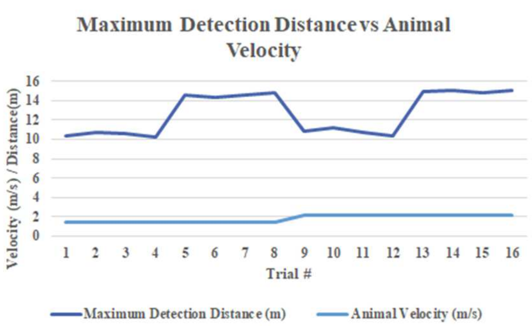

Fig. 5. Maximum Sensor Detection Distance vs. Wildlife Crossing Velocity

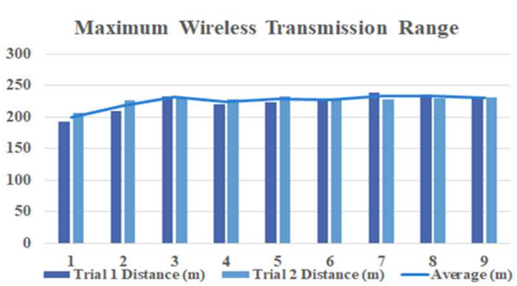

Fig. 6. Ad-Hoc WiFi Module Data Transmission Range

C. *Wildlife Image Processing and Machine Learning Model Performance*

To ensure testing model accuracy, the test set contained 10 select images of each of the 6. Besides a baseline model with no image processing techniques applied, different image filters and blurs techniques such as the Gaussian blur, Median blur, and Laplacian edge sharpening filter are tested and compared to improve the accuracy and training efficiency. Each of the methods implements unique modifications to the image via background blending, overall muting, and gradients respectively. The accuracy comparison results are demonstrated (Fig. 7), which indicated that the Laplacian edge sharpening model is the most accurate model at a 95% test prediction accuracy. Successfully taking the gradient and preserving shape amongst these four categories, the Laplacian filter applied CNN will be used for future image processing. (Fig. 8).

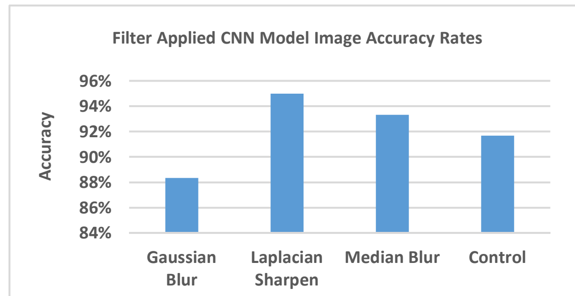

Fig. 7. Bar Chart Comparison of Model Performances

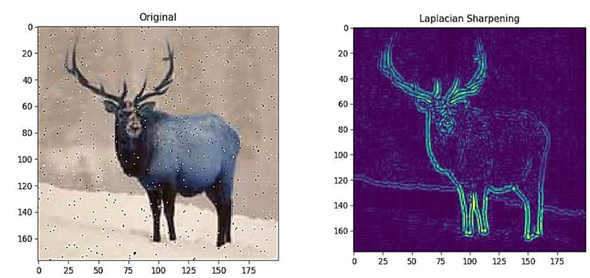

Fig. 8. Resultant Laplacian Filter Image

D. *Wildlife Migration Pattern Generation*

For effective understanding and use of SWS collected data amongst government agencies (like ODOT), road ecologists, and wildlife researchers, there is a need to create a visual map with detected wildlife activity hotspots based on the animal appearance frequency detected and identified by the SWS. A python script was developed, using GMap and folium library which plots unique latitude and longitude points on a global map for detected wildlife activity.

Due to inadequate real in-field data available for wildlife activity pattern prediction analysis. In this case study, an existing 2008 activity database[6] is used to demonstrate the longstanding application of the SWS to track and monitor animal WVC and activity hotspots and furthermore to predict migration patterns to assist road ecologists and government infrastructure planning. In the study, 3 species of animals: black-tailed deer, Roosevelt elk and coyote, are tracked across 6 locations in Oregon: Bend, Ontario, Roseburg, Medford, La Grande and John Day, during 4 seasons of 2008 with a number of occurrences sighted. Each species has a unique heat color code with darker shades of a color and bigger bubbles indicate dense activity while light shades and a smaller bubble show lighter activity at a location. Utilizing python raster visualization package Folium, the maps generated are interactive so that users can click on each bubble to access information regarding location, species, and occurrences. Furthermore, overlapping all

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4 maps can display a clear migration pattern over time as demonstrated in Figure 9.

It is interesting to see that red (Elk) and green (Deer) activity occurred intensively during fall season which makes perfect sense. As the days grow shorter, Oregon deer are beginning their seasonal migration. That makes October and November peak months for collisions between vehicles and wildlife.

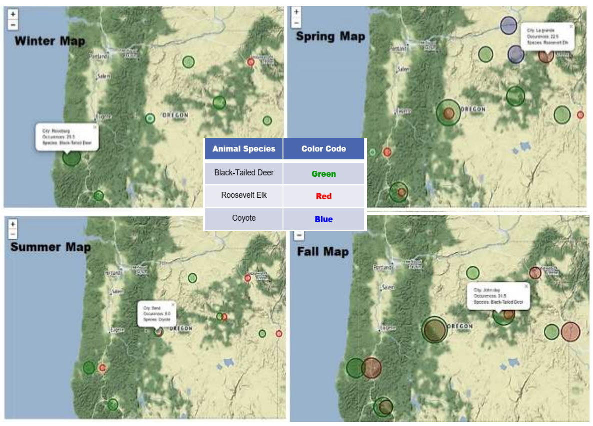

Fig. 9. Demo of Interactive Wildlife Activity Maps of Oregon in 2008

IV. Conclusions and Future Work

The SWS prototype effectively demonstrates the integration of IoT technology to minimize roadkill accidents. In addition, machine learning methods used assist wildlife conservation efforts by identifying animal species, monitoring animal activity, and indicating animal seasonal migration patterns. Through comparison of three different computer vision techniques to a control method, the highest accuracy of 95% in machine learning model performance was achieved through application of a Laplacian filter on the final test set.

Future work for this project focuses in-field testing and further improvements to the machine learning model ac-curacy. Training images had a limited scope of lighting, animals, and positioning. For future neural network model improvements, a wider variety of animal species will be used to grow wildlife identification capacity. In addition, testing of closed-circuit television or thermal imaging will be conducted to expand on more effective wildlife activity capturing systems involving live video wildlife recognition. Furthermore, wireless capabilities are to be improved by utilizing an app-based system and connecting to the on-board driving assistance systems wirelessly for live traffic feed information on the go.

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