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E-Wild Life Alert: Tackling the Human-Wildlife Conflict Problem

Eliel Kundai Zhuwankinyu
kundaieliel12@gmail.com

Sibonile Moyo
sibonile.moyo@nust.ac.zw

Catherine Chivasa
catherine.sibanda@nust.ac.zw

Smart Ncube
smart.ncube@nust.ac.zw

E-WildLife Alert: Tackling the Human-Wildlife Conflict Problem

Research Paper

Elliel Zhuwankinyu
Department of Computer Science
National University of Science & Technology
Zimbabwe
kundaieliel12@gmail.com

Sibonile Moyo
Department of Informatics & Analytics
National University of Science & Technology
Zimbabwe
sibonile.moyo@nust.ac.zw

Catherine Chivasa
Department of Informatics & Analytics
National University of Science & Technology
Zimbabwe
catherine.sibanda@nust.ac.zw

Smart Ncube
Department of Informatics & Analytics
National University of Science
Zimbabwe
smart.ncube@nust.ac.zw

ABSTRACT

Depletion of resources meant for both human and animal survival leads to competition for these. Human-wildlife conflict (HWC) occurs when these two parties compete for resources such as space, water, and food. If not properly managed, HWC can lead to loss of livelihoods and even loss of life. This paper discusses the design and development of an E-Wildlife Alert application that uses machine learning to detect dangerous animals. Using the Design Science Research method, a convolutional neural network is trained to build an artifact that detects five dangerous animals from an African context. The artifact is mounted on a robot that propels it around, providing a 360 degree turn for the image capturing camera to get a full view of the environment. On detecting any object in the way, the robot turns to avoid the obstacle. The E-Wild Life Alert application is able to detect five dangerous animals with an accuracy of up to 98%. On detecting any such animal in the vicinity, the application sends an SMS to a phone number in the system, logged as wildlife parks officer. This system would be useful, first to humans bordering areas with dangerous animals, as it protects them from these. Secondly, the tourism industry can benefit from the application as it reduces the number of wildlife killed on straying. In the long run, such an application is beneficial to nature in terms of conservation, promoting species diversity.

Keywords

Human-wildlife conflict, convolutional neural network, image recognition, e-wildlife alert.

1. INTRODUCTION

Human-wildlife conflict (HWC) refers to clashes between humans and wildlife. Such clashes often occur when these two groups share common borders. Carnivorous wildlife poses a danger to both human and animal life (Braczkowski et al., 2023). The HWC problem is prevalent in developing economies where there are limited resources to enclose dangerous animals, leaving these to wander to human habitation. In most of these countries, the conflict mainly occurs where a significant percentage of a nation's population lives in rural areas and amongst or bordering wildlife areas, with livestock being the main economic activity of livelihood for these populations (Anand & Radhakrishna, 2017). In such areas, conflict is usually due to competition for space caused by increased human and animal populations (Chen et al., 2019). Climate change has worsened the situation, as apart from competing for space, humans and animals now compete for scarce resources such as food and water (Bautista et al., 2023; Göttert & Starik, 2022; Griffin et al., 2022).

HWC is detrimental in that it may result in loss of human life and domestic animals, and the destruction of crops (Bautista et al., 2023). In Zimbabwe wildlife has caused trauma and a lot of destruction among communities living in the Save Valley, with most of these having to take turns to guard their homesteads both during the day and night. In tackling this problem, we seek to design a machine learning-based prototype that can be used to detect dangerous animals. The main objectives set for the prototype are: (1) to identify a defined set of wild animals deemed as dangerous, (2) to send SMS message notifications to the nearest ranger notifying them of the identified animal, (3) to make 360-degree angle movements to allow the camera to have a complete view of a site and (4) to be able to avoid obstacles to protect the prototype hardware from damage. The prototype is tested in a simulated environment, with the application deployed as an embedded system, mounted on a robot that continuously turns as a means of scanning the environment. In the following sections, we review literature related to efforts made so far in tackling the problem of HWC in Section 2, in Section 3 we discuss the design of E-Wildlife Alert and its implementation, Section 4 discusses a snapshot of the results, Section 5 concludes the paper giving recommendations for live testing and deployment of the system.

2. RELATED WORK

Livestock and crop production are an important component of agricultural activities in developing economies. In Africa, livestock and crop production are the most prevalent farming activities, as they significantly contribute to food security and poverty reduction (Myeki et al., 2022). Poverty eradication (Goal 1) and hunger elimination (Goal 2) are some of the sustainable development goals of the United Nations (United Nations, 2015). In Zimbabwe for example, cattle perform several economic and cultural activities that include provision of draught power, support for ritual activities, milk and meat production, manure production, and provide a form of social security. Animals such as goats and sheep are also reared for economic purposes, with several breeds having been tried in several parts of the country. However, despite all these economic and cultural benefits that livestock has on people's livelihoods, most Southern African communities are in danger of the conflict that exists with wildlife. Research shows that livestock predation usually occurs outside wildlife reserves bordering human occupied landscapes (Anand & Radhakrishna, 2017; Göttert & Starik, 2022; LeFlore et al., 2019). Increases in human population, and diversity in livestock, have recently expanded the problem of human wildlife conflict to urban areas (Anand & Radhakrishna, 2017). Livestock predation results in loss of livelihoods, and should be reduced if not avoided. If left unchecked, HWC results in species depletion and environmental imbalance. In the next sections we discuss some of the measures used to reduce HWC.

2.1 Human-Wildlife Conflict Management

The HWC problem has attracted a lot of attention from several stakeholders. A number of proposals to deal with HWC have been put across. Some have been effective, but the problem still remains an open debate. In this section, we focus on some measures that have been implemented from a Zimbabwean perspective.

2.1.1 Fencing

One of the traditional means of dealing with HWC is to fence off the wild animals. This prevents wild animals from wandering to the regions of human populations, and livestock and humans from wandering into areas reserved for wildlife. Fences can either be electrified or non-electrified. Non-electrified fences are prone to both human and animal bypassing. Electrified fences have been found to be more effective in keeping the boundary between the two parties resulting in improved agricultural productivity (Matata et al., 2022). However, both electrical and non –electrical fences have their down side. Electrical fences may be lethal (Matata et al., 2022), while non-electrical fences may be stolen or bypassed by occupants from either side of the fence if poorly maintained (Kamdar et al., 2022). Fence maintenance can prove to be too costly for developing economies. In Zimbabwe, most fences have since disappeared leaving animals to wander to where they are not wanted. In some cases, where fences used to prevent animals from interfering with traffic along the roads and railway lines, these have been vandalized, leaving animals to wander to roadsides resulting in increased road accidents.

2.1.2 Communal Areas Management Programme *(CAMPFIRE)*

The Communal Areas Management Programme for Indigenous Resources (**CAMPFIRE**) is a Zimbabwean community-based natural resource management program. It gives local people in a community the authority to manage wildlife in areas that border their communities. The authors in (Gandiwa et al., 2014) realized that the CAMPFIRE program significantly reduced the impact of HWC. Communities with a smaller conservation area and larger group size are better off in terms of fostering cooperation in managing their natural resources than communities with a larger conservation area and smaller group (Ntuli & Muchapondwa, 2018). In such cases, the human population is larger than the animal population and hence can effectively stop wild animals from interfering with the human population. The success of the CAMPFIRE project has thus been based on these two factors, that is the size of the human population versus the size of the conservation area.

2.1.3 Unmanned Aerial Vehicles (UAVs)

Unmanned aerial vehicles (popularly known as drones) are now increasingly being used in wildlife conservancy for monitoring, tracking and statistical purposes in areas sometimes difficult to reach by humans. Drones have been popularly used to replace light aircraft in animal statistics, as they can be made to fly at a much lower range (Corcoran et al., 2021), enabling the identification of smaller species. These technologies minimize human effort, increase accessibility and collect accurate information (Mazumdar, 2022). In their basic designs, these UAVs are heavily dependent on the human element for the interpretation of the captured imagery. This scenario has its disadvantages that come from human error, labour intensity, and slowness among others. The UAVs’ capabilities can be enhanced through automating the image processing and using machine learning technology to interpret the image instead of the human.

2.1.4 Machine Learning Based HWC Techniques

With the advancement in technology, image processing has drastically improved. This brings about a plethora of options towards animal detection. Studies have sought to use machine learning to automatically detect dangerous animals, with the hope of deterring them from crossing set boundaries, or alerting concerned authorities, in case of unauthorized crossings. In (Chen et al., 2019) the authors use deep neural networks to classify animals. The authors were able to classify 6 animals achieving an accuracy of 90.3%. Our study builds on these authors' study which was classifying badgers, birds, cats, foxes, rats and rabbits (Chen et al., 2019).

Convolutional neural network (CNN) is a subset of artificial neural networks which uses perceptron, a machine learning algorithm for supervised learning to analyze large amount of data. In another study (Gomez et al.,2016) the authors developed a convolutional neural network to identify wild animals from the world's largest camera trap project. The overall accuracy for animal identification was estimated at approximately 57%.

While the above studies may have laid the much needed groundwork in animal image processing, they fell short of contextualizing the study to wildlife posing danger to communities in the Southern African setting. In Zimbabwe we classify dangerous animals to include the elephants, lion, leopard, hyena, and the African crocodile. In the next section we discuss study design.

3. E-WILDLIFE ALERT DESIGN AND IMPLEMENTATION

3.1 Method and Tools

We use Design Science Research Methodology (Vaishnavi et al., 2017) to design the E-Wildlife alert application. Following the stages of this research, first, a problem is defined, an artifact is suggested and designed, implemented, and finally evaluated, giving a conclusion regarding knowledge contribution. In this paper, we discuss the first stages of the E-_wildlife artifact design, i.e., problem identification, its suggested objectives, design and the implementation of the prototype. The main problem being tackled is the ineffectiveness and human error emanating from the existing technologies. We use turn to machine learning for the solution and use the convolutional neural network (CNN) to build the animal classifier. The main purpose of the classifier is to automate the identification of the dangerous animals. We step through the processes of normalizing the image pixel values of input images; one-hot encoding for the representation of categorical data; building a model architecture; and training the model in preparation for identification.

The training of the CNN classifier was programmed using Python in Google Co-lab. Training a neural network requires a Graphic Processing Unit (GPU). Google Co-lab offers a free GPU online and makes the development less costly. It also enables developers to work on the cloud without installing software on their machines. The inference of the machine learning model and its labels is done on the Raspberry Pi model 3b+. Raspberry Pi model 3b+ offers 4.2 Bluetooth, dual-band Wi-Fi feature, more improved processor and a 2.5 A power. Thonny is a default Integrated Development Environment (IDE) in the

Raspberry Pi. It is the environment on which the Python script that calls the machine learning model and the SMS API is programmed.

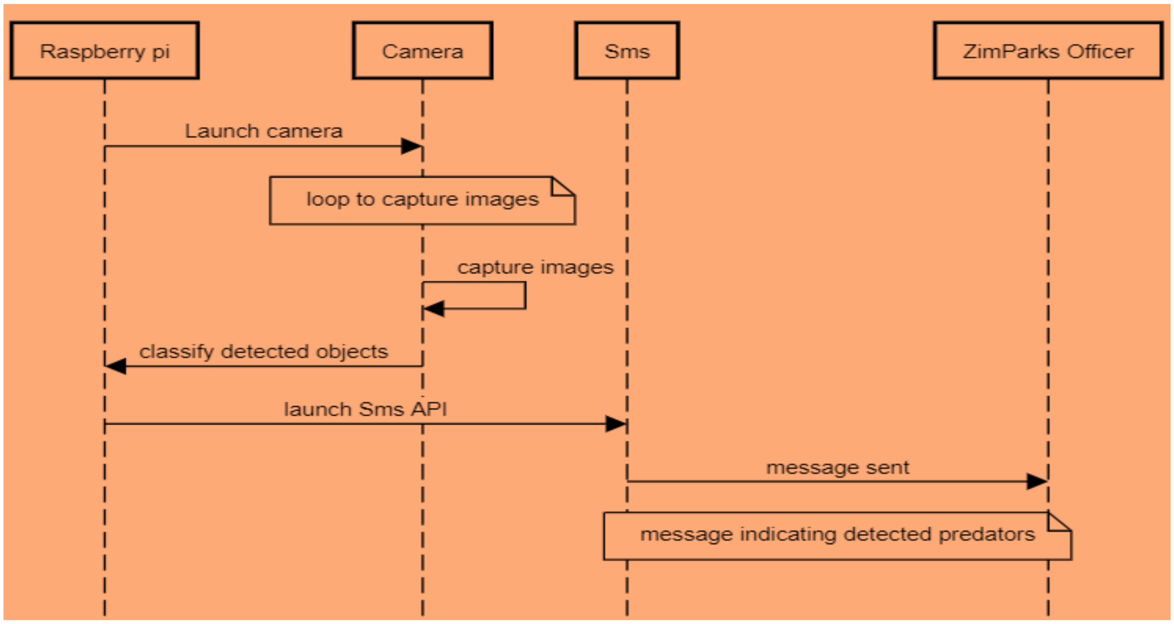
3.2 Design and Implementation
For the wild life alert prototype, we have developed a desktop application that provides real-time video footage for object detection. The E-Wildlife Alert model runs on the Raspberry Pi and the evaluation is done using the Raspberry Pi camera. We developed a Python script which contains the whole program that allows for the real time video footage scanning and performs object detection. To simulate alerts, we develop a short message service (SMS) Application Programmable Interface (API) that is embedded within the Python script that calls the machine learning model so that once an object of interest is detected, the SMS notification is sent to the responsible recipient.

We have also designed an obstacle avoiding robot that carries and protects the system. When the detecting camera is set at one stationery position, it can only capture video footage at 180-degree angle. To achieve a 360-degree angle of camera turns, we developed a robot that uses an ultrasonic sensor to detect obstacles on its way. This also measures the distance of a target object so that once it reaches that distance; it turns clockwise to avoid collision with the object. In this case, a circular boundary is set so that when the robot moves in a particular direction, it always turns clockwise to avoid colliding with the boundary. In this way, the camera on top of the robot is able to have an angle of 360-degrees view as the robot moves clockwise avoiding collision with the boundary.

The following E-Wild Life Alert objectives guide this design. It should be able to identify wild animals, upon which an SMS notification should be sent to the nearest wildlife parks officer. The classifier is mounted on a robot, which should be able to make 360-degree angle movements to allow the camera to have a broader view of a site. At the same time the robot should be able to avoid obstacles to protect the hardware from being trampled over. Figure 1 depicts the sequence of events that lead to the fulfillment of the desired activities.

Figure 1

Sequence Diagram for E-wildlife Alert



The Rasbery Pi lauches a camera, which captures an image of an animal. The image is classified by the same Rasbery Pi. If a dangerous animal is detected, an SMS API is launched to generate an SMS message which is sent to the ZimParks Officer. The system thus alerts relevant authorities of the pending danger.

3.3 Data Collection

Data for training of the network was obtained from the Common Objects in Context (COCO) dataset consisting of 1000 animal images for training and over 20 classes for wild animals. This is an open source repository that hosts large scale object detection imagery. We deem it appropriate for this research as it stores data as images which can be identified with much ease

Figure 2

Data Set Preview

The training data includes both input data and its corresponding labels. Testing data, on the other hand, includes only input data, not the labels. The testing data is used to assess how well the model was trained, and to estimate model properties. A training test ratio of 0.8:0.2 was used.

4. RESULTS

The model was run on the raspberry pi and the highest accuracy recorded was 98%. The model was trained to identify a lion, African crocodile, leopard and a hyena. The model was able to detect the crocodile with a great accuracy of 99% and a detection time of 265 milliseconds. The detection of the Leopard had 95% accuracy, while that of a lion and a hyena had both a highest accuracy of 98% with times of 265,65 ms and 264.4 ms respectively. Figure 3 shows samples of leopard and hyena detection, together with their accuracy and time taken to complete the detection.

Figure 3

Detecting a leopard and a Hyena

An obstacle avoiding robot was designed to move the classifier around. The robot was mounted with sensors to detect any obstacle within 250 cm. On detecting an obstacle, the robot turns away from the obstacle using the servo motor mounted on the robot. The code listing below controls the robot producing a 360-degree angle turn, the robot was designed with high wheels to enable clearance on any items on the ground, not detected as obstacles. Figure 4 shows the robot designed to provide the model with a 360-degree view. The high wheels provide good ground clearance.

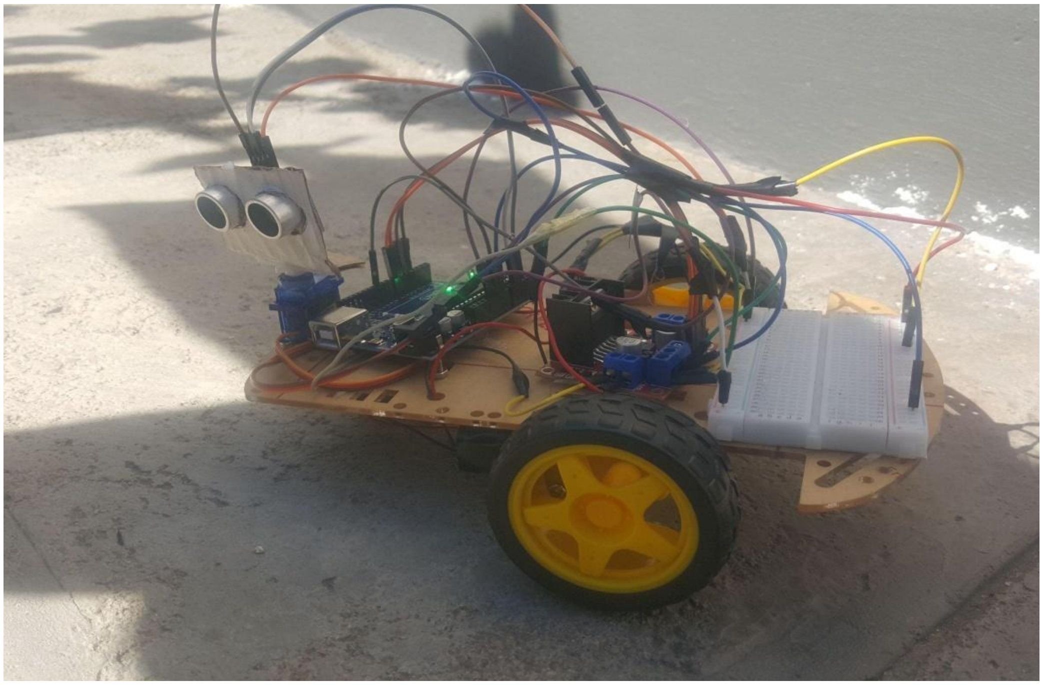
```
int lookRight(){
  servo_motor.write(50);
  delay(500);
  int distance = readPing();
  delay(100);
  servo_motor.write(115);
  return distance;
}

int lookLeft(){
  servo_motor.write(170);
  delay(500);
  int distance = readPing();
  delay(100);
  servo_motor.write(115);
  return distance;
  delay(100);
}

int readPing(){
  delay(70);
  int cm = sonar.ping_cm();
  if (cm==0){
    cm=250;
  }
  return cm;
}
```

Figure 4

Obstacle avoidance robot housing the E-Wildlife Alert Application



The E-Wildlife Alert application was tested in a simulated environment, generated based on the literature. The animal video streams were generated from a desktop. Apart from identifying animals generated from the video streams, the classifier was also able to identify images of animals printed on paper.

5. CONCLUSION

We have managed to train a convolutional neural network to identify animals classified as dangerous, with an accuracy of up to 98%. This level of accuracy is consistent with that achieved by other researchers in image identification (Chen et al., 2019; Tian, 2020). Our contribution to theory is a classifier that can be used to identify dangerous animals in an African context. While CNN has been used previously to detect herpetofaunal species such as frogs, lizards, and snakes (Sazida et al, 2023), and also in detecting nocturnal and evasive animals, we did not find any work that uses CNN in the manner that we have used it. Other researchers can build on this classifier to come up with a classifier that can identify a set of animals of interest.

With the classifier mounted on an obstacle avoiding robot we have managed to move the classifier around, while avoiding any obstacle. Obstacle avoidance was designed to mimic obstacles in a real life environment. On detecting any wildlife used in this study, the system was able to send SMS messages to numbers logged in the system.

As future work we intend to test the E-Wildlife Alert application in a live environment such as a natural wildlife park with the model mounted in a drone. This will serve to prepare the model for deployment in a live environment. The E-Wildlife Alert application will be useful in any environment where there is a need to alert wildlife officers of any stray animals. This would also benefit the general public as they are protected from stray carnivorous animals. Livestock will also be saved. The tourism industry will also benefit, as this means reduction in the killing of stray animals.

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