Human-Wildlife Conflict Early Warning System Using the Internet of Things and Short Message Service

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Abstract-Human-wildlife conflict (HWC) is an important challenge to communities living in areas bordering wildlife game parks and reserves. It is more evident in the United Republic of Tanzania, whose economy depends on wildlife tourism. This paper proposes a low-cost and low-power early warning system using the Internet of Things (IoT) and Short Message Service (SMS) to support HWC respond teams in mitigating these challenges. The system comprises three primary units: sensing, processing, and alerting. The sensing unit consists of a Passive Infrared (PIR) sensor, a Global Positioning System (GPS), and a Raspberry Pi camera. The PIR sensor detects the proximity of the animal using the heat signature, GPS senses and records the current location, while the Raspberry Pi camera has the primary purpose of taking a picture after the PIR sensor detects the proximity of the animal. The processing unit with a Raspberry microcomputer performs data processing and image inferencing using the You Only Look Once (YOLO) algorithm. Last is the alerting unit, which includes a Global System for Mobile (GSM) communications module for sending SMS messages to the human-wildlife conflict response team and the nearer community response team leader whenever wild animals are spotted near the park's border. The system detects, identifies, and reports the detected wild animals. The GPRS provides internet connectivity to support data collection, storage, and monitoring in the cloud.

Keywords-camera trap; edge machine learning; Raspberry Pi; human-wildlife conflict; early warning system

I. INTRODUCTION

Human-wildlife conflict (HWC) is an interaction between humans and wild animals with negative consequences. The typical results of the conflicts include crop damage, and injuries or deaths of livestock, humans, and endangered wildlife species [1]. HWC is caused primarily by the human population increase, which causes loss of wildlife habitats due to the pressure to increase agricultural land [2]. HWC is a serious issue in Tanzania and has been rising over the years. The HWC data in Tanzania from the wildlife division have shown a rising trend, as shown in Table I.

TABLE I. HWC STATISTICS IN TANZANIA [22]

Year	Deaths	Permanent injuries	Temporary injuries	Licestock deaths	Crop damage (acres)
2012-13	69	23	38	46	1518
2013-14	61	31	49	93	4046
2014-15	59	20	41	107	6786
2015-16	102	20	78	64	8924
2016-17	132	30	54	130	4567
2017-18	380	20	29	149	5016
2018-19	266	60	149	203	10547
Total	1069	204	438	792	41404

Like most economies in Sub-Saharan Africa, the Tanzanian economy majorly relies on agriculture and wildlife tourism, which contribute to the GDP about 30% and 17% percent. Moreover, tourism is the main contributor of foreign currency, therefore, it is an important sector of the economy [3]. The government of the United Republic of Tanzania has adopted some strategies to mitigate HWC by getting real-time information about HWC. For example, collaring utilizes the IoT to geo-fence movement of large body species, such as elephants, known for causing HWC or endangered species being poached. Another method is using hotline numbers to report HWC incidences. These methods have significantly

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improved the efficiency in handling HWC. However, continuous monitoring of wildlife using collaring has been proven to be expensive to install and operate due to its networking requirements and the equipment's initial cost, especially in remote areas with poor network coverage and low population density [4], while a hotline system utilizes a reactive approach, hence there is a need for a cheaper and proactive approach. Therefore, a low-cost camera trap was developed. Camera traps have gained popularity in wildlife monitoring and surveys because of their efficiency in collecting wildlife images without monitoring [5, 6]. They need slight improvements, such as the ability to use microcomputers which support machine learning algorithms to support early warning systems. The phone use has become essential, even for for pastoral communities, therefore such a system could be used by the locals [7].

Different researches have tried to come with different early warning systems. Authors in [8] developed an early warning system using motion detectors and passive infrared sensors to detect wildlife and notify residents through loudspeakers and mobile apps. However, the system is not suitable for the human-wildlife response teams in Tanzania who need wildlife identification to determine the method of responding. Authors in [9] developed a camera trap system that used a PC for image inferencing. However, it needs bandwidth to transmit a lot of data between the end node device and the PC, hence it requires more power to perform inferencing. Authors in [10] developed a machine learning model that accurately identified elephants with accuracy up to 94%. The system used a convolution neural network to develop its model. Authors in [11] developed a seismic sensor system as an early warning system to detect and report elephants.

II. MATERIALS AND METHODS

A. Case Study

The studied area was the Ngorongoro conservation area and the Tarangire national park. These parks were chosen because they receive significant complaints concerning HWC.

B. Data Collection

The equired images to develop the machine learning model were collected by taking pictures in the parks, while other photos were borrowed from the Tarangire national park authorities. Three hundred images of each species were gathered. All the images were preprocessed by labelling, rescaling, and augmenting. Each image was labelled correspondingly to the 6 classes of considered animals: elephant, lion, leopard, zebra, buffalo, and rhino and their localization in the image.

C. Image Preprocessing

The images were scaled to 214×214 before being fed to the model. Augmentation is a technique used to generate new images by a random transformation of existing data. It decreases the chances of overfitting. Augmentation can increase data up to 50 times.

D. Deep Learning

Computer vision is an important field of study in artificial intelligence that enables computers to detect and identify objects. Object detection methods are usually three-stage processes: proposed region selection in the image using bounding boxes, feature extraction, and then the trained classifier is used to perform classification. The basic approaches to machine learning in images are traditional machine learning and deep learning. Deep learning has better performance than machine learning when a lot of data and many parameters are involved. A Convolutional Neural Network (CNN) is a powerful data mining algorithm used in deep learning classification problems because it has higher accuracy with large datasets [12]. Object detection in CNN is divided into region-based detection and regression object detection methods. Region-based detection algorithms perform better in object detection accuracy, but have slow operation. These algorithms are Region-based Convolutional Neural Network (RCNN), Fast Region-based Convolutional Neural Network (fast RCNN), and Faster Region-based Convolutional Neural Network (faster RCNN). On the other hand, the regression object detection methods generate a region proposal network and then classify the region simultaneously producing results faster than the region-based detection. These methods are Single-Shot Detectors (SSD) and You Only Look Once (YOLO). The YOLO [13] algorithm is faster than SSD in object detection. Moreover, it can detect small objects accurately, it is therefore suitable to our scenarios due to the microcomputer usage in which the results are required promptly to reduce the power consumption of the camera trap.

E. Proposed Model

The YOLO detector usually divides the image into grids and then performs prediction to get the location of the object. The next step is intersection-over-union to predict the bounding box to find the truth box. Finally, the bounding box's threshold is determined to obtain the final results. The architecture used is darknet-53. The training was done using a batch size of 512, ReLU activation, and 40 epochs. The size of the input image is 214×214×3 pixels and after 3 pooling and 6 convolutions, the size is shrunk to 21×21×128 pixels for the output feature maps. Further convolutions produce a 1×1×4096 neuron [14]. The proposed model achieved training accuracy of 90% and validation accuracy of 78%, as shown in Figures 1-2.

F. The TinyML Model

The collected images were converted into a matrix in the edge impulse Graphical Processing Unit (GPU) server. All photos were annotated with their respective labels. Label mapping was done to detect an object from the annotated images. The label mapping was transformed to the TensorFlow file format of the trained model to produce an interface graph that would classify pictures. The graph was converted into a TensorFlow lite file that the Python program would infer from when detecting objects in the images [15].

G. System Architecture and Design

The system architecture has 3 major units: sensing, processing, and alerting. The system block diagram is shown in Figure 3.

1) Sensing Unit

The main sensing unit consists of a Passive Infrared (PIR) sensor, a Raspberry Pi camera, and a GPS module. The PIR sensor is used to detect the presence of wildlife in its proximity using its heat signatures [16] to perform its role, therefore it can work under all light conditions [17]. The Raspberry Pi camera [18] is used to take the picture after its activation following the presence of wildlife. The GPS module is used to accurately determine the device's current location using GPS coordinates [19].

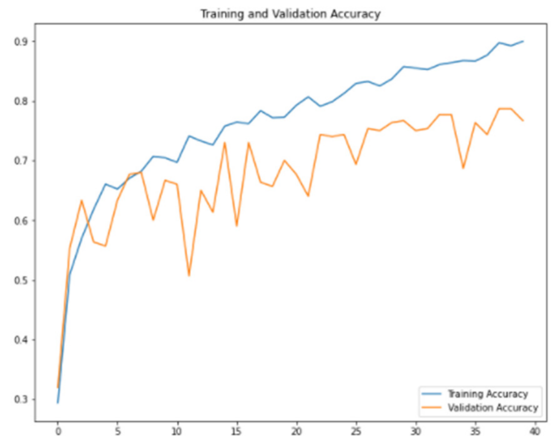

Fig. 1. Taining and validation accuracy.

Fig. 2. Training and validation loss.

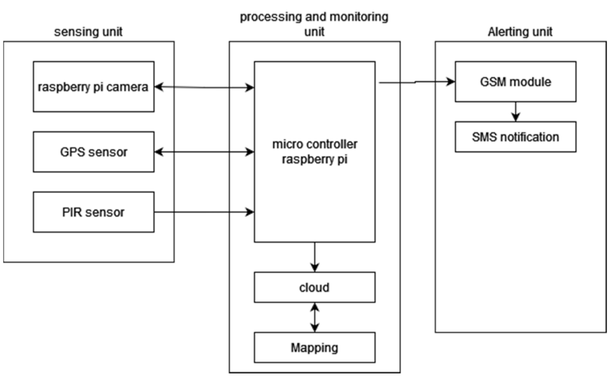

Fig. 3. System block diagram.

2) The Processing Unit

A Raspberry Pi equipped with the YOLO model was used to analyze the image taken by the camera and to detect and identify wildlife. The Raspberry Pi used is a low-power consuming microcontroller [20]. The reason for choosing the Raspberry Pi was its low power consumption for its reasonable processing speed.

3) Alerting

After wildlife classification and identification, SMS messages were sent containing the google map location link of the wildlife along with the name of the animal to the relevant personnel. The link is used to visualize the location of the wildlife identified [21].

H. System Configuration

The system components were configured to the Raspberry Pi development board. All the components were connected to the Raspberry Pi.

I. Programming Tools

The system was developed in Python to control all sensing units and the alerting unit. The processing unit processes data using the YOLO model packaged into the TensorFlow lite file. After object detection and identification, the alerting unit sends the data to the intended destination. Figure 4 shows the flowchart of the steps of the proposed model.

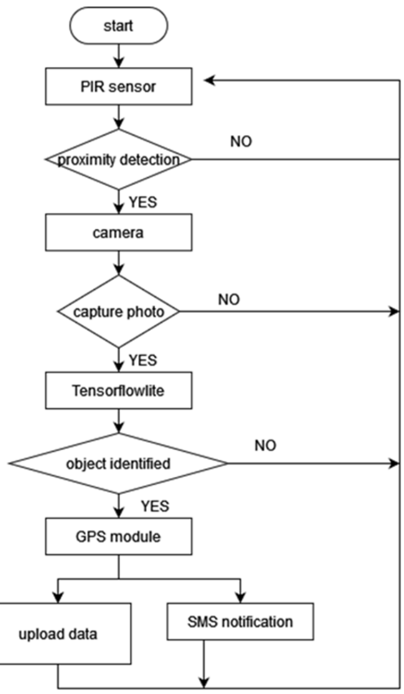

Fig. 4. System flowchart.

J. Testing

1) Model testing

The YOLO model was tested using the park data and achieved 98% detection accuracy as shown in Table II.

TABLE II. MODEL TESTING CONFUSION MATRIX RESULT TABLE

	Buffalo	Elephant	Leopard	Lion	Rhino	Zebra	Uncertain
Buffalo	100	0	0	0	0	0	0
Elephant	1.7	94.8	0	0	3.4	0	0
Leopard	0	0	100	0	0	0	0
Lion	0	0	0	100	0	0	0
Rhino	0	3.1	0	0	95.3	0	1.6
Zebra	0	1.1	0	0	0	98.9	0
F1 Score	0.99	0.95	1.00	1.00	0.96	0.99	

2) *System Testing*

The system testing was done in the lab. The system was tested by directing the camera to a picture of a wild animal on the screen and then swapping it with different pictures of objects and animals. The system identified the animals and uploaded data to the cloud.

III. RESULTS AND DISCUSSION

The results presented here show the work from testing the camera trap. The camera was developed using a Raspberry Pi microcomputer, a PIR sensor, a GPS module, a Raspberry Pi camera, and a GSM module. The prototype of the system is shown in Figure 5. The sensing units include the PIR sensor that activates the camera when it detects the proximity of an animal from its heat signature. After the picture is taken, the image is sent to the model packaged into the TensorFlow file to perform inference to detect and identify the animal in the picture. If the animal is identified, an SMS is sent to the listed numbers belonging to the HWC response team and the community human-wildlife response group. The model was able to detect and identify wildlife with good accuracy. It detected different species as shown in Figures 6 and 7.

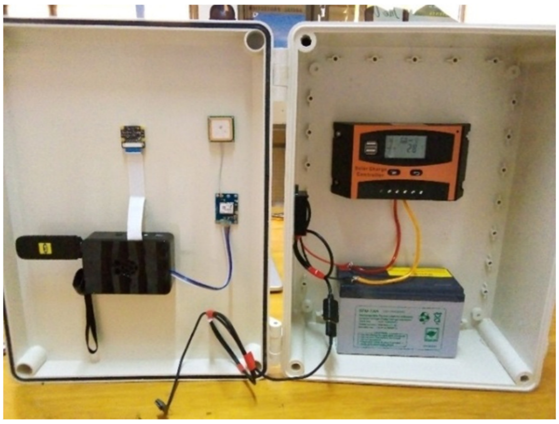

Fig. 5. System prototype.

It was observed that when the object was placed at a close distance from the camera, it was accurately identified. However, if it was placed too far or too near, the system tended to misidentify the animal or even not identify it at all. The recipient of the SMS message is determined based on the species of the identified animal. If the wild animal is dangerous, a message is sent to both the community response team leader and the HWC response team. If it cannot cause HWC, but is an endangered wild animal, a message is sent to the HWC response team only, while if the wild animal cannot cause HWC and it is not a endangered one, no message is sent. The SMS contains the name of the species of the wild animal and the google map link location of the wild animal.

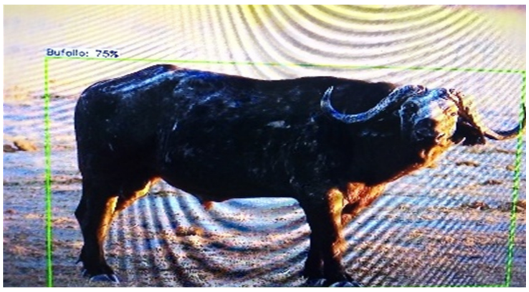

Fig. 6. Buffalo detection.

Fig. 7. Elephant detection.

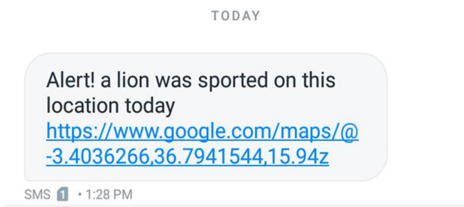

Fig. 8. A received notification message.

A web-based system was developed with the primary purpose of monitoring and managing data from the sensor nodes. It is accessible by a web browser. Park rangers and park managers are the only people allowed to use the system to access the park's wildlife spotting data from the database. The system works best if the camera traps are placed at a distance of 40 meters apart to ensure their efficiency. This distance is the combination of the efficiency of the PIR sensor and camera distance of focus that come into play. In our case study area, it is best to place the cameras in places with weak fences and near areas with high human population to reduce the cost of the whole project.

A. *Discussion*

The conducted experiments in selected places proved that the system can monitor the movement of wildlife and rapidly report the identified dangerous or endangered wildlife species.

The processed data were sent to the server for visualization and tracking was conducetd by using a web application dashboard.

IV. Conclusion and Recommendations

The proposed low-cost early warning system was developed to report incidents that may cause HWC using SMS. It is suitable for use by the park and community HWC response team members living in HWC-prone areas. This system can support the rangers patrolling the parks by providing insightful information about wild animal locations fast. The system allows remote real-time wild animal monitoring from the park's base station. The system is stand-alone and can work for different occasions by modifying system components and the detection model to fit in different situations, such as tracking livestock and protecting houses against theft.

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