Real-time Animal Detection and Prevention System for Crop Fields

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Real-time Animal Detection and Prevention System for Crop Fields

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Abstract: Every year, crop damaged by wild animals is dramatically increasing in Sri Lanka. It often poses risks to humans and animals. Since more and more wild animals are causing damage to their cultivation; humans could not tolerate it. Therefore, they require an effective mechanism to overcome this situation. With that background, the objective of this study is to detect wild animals before entering into the crop fields and implementing appropriate scare-away mechanisms in real-time. The presence of the animal will be sent to the farmer via a mobile application. In this study, two Convolutional Neural Network (CNN) classification models have been developed using the transfer learning approach with the VGG-16 as a pretrained model to detect elephants, wild boars, and buffalos. Both two models were combined and runs on Raspberry pi, which acts as the processing unit for the system, captures the images of animals, and predicts it. Whenever the presence of the animal senses by the thermal sensor which is installed on Arduino, it sends a trigger to capture the image. Based on the prediction sudden flashes of light, ultrasound, and bee sound will be produced to scare away the animals. The mobile application was developed using react native which is used to alert the user about the animal, connected through the Firebase database. The findings of this research indicate that the accuracy rate of the classification model is 77 percentage. This system significantly reduces human-animal conflict in crop fields by automatically implementing scare-away mechanisms based on the prediction.

Keywords: Animal Detection, Scare-away mechanism, User Alert, Convolutional Neural Network, IOT

Introduction

In Sri Lanka, agriculture is one of the major economic forces. In 2018, the Gross Domestic Product (GDP) rate for agriculture was 7.8 percentage and generated Rupees 555,679 million. (Central Bank of Sri Lanka, 2018) Every year, thousands of human-animal conflicts caused numerous deaths, physical injuries, and loss of properties. Mostly, human-animal conflicts occur when animals raid crop fields in search of food. In particular, more deforestation contributed to a reduced amount of habitat for the animals, and they are forced to come out of their range to search for new habitats and food in farmlands. In fact, according to the agriculture ministry of Sri Lanka, it has been confirmed that 40 percentage of the annual crop is destroyed by wild animals. (Colombo Page, 2019) Commonly, crops are damaged by elephants, wild boars, monkeys, peacocks, squirrels, and porcupines. There have been many incidents in the past where the conflict between humans and animals has caused serious damage to crops and resulted in the loss of the economy and the lives of farmers and animals in Sri Lanka. Mostly, Farmers are depending on various methods which are traditional, legal, and some illegal methods to overcome wild animals' intrusion. For instance, they use gun fires and firecrackers to keep elephants away. In Sri Lanka, 225 elephants have been killed by farmers annually since 2008 and elephants have killed about 60-80 people annually. (Jayantha, 2020) Illegal methods like trap guns, snares, crackers, and explosives are still in practice to kill wild boar, which also kills many other animals and even humans. Electrified wires are laid on paths used by animals, accidentally, humans get hurt when they come into contact with these electrified wires sometimes. Like these, various prevention methods are used against various animals. Some may be efficient and others result in injury to both humans and animals. Moreover, the prevention mechanism which was used by farmers is very expensive to implement as well as harmful to animals and humans' life, yet farmers often kill animals to protect their crops and life. To solve the problem, the system was developed that can detect wild animals entering the crop fields using CNN and implementing appropriate scare-away mechanisms in real-time. It will be done by alerting farmers through a mobile application about the presence of wild animals in their fields. The system will significantly reduce human-animal conflict in crop fields. Briefly, this system has been developed to minimize damages in the crop field, loss of human life, and destruction of animals. The scare-away mechanism helps to reduce the injury and death of animals in an eco-friendly manner. On the other hand, it protects the crop fields from harmful animals.

Background and Related Works

A. Animal Detection

Most of the animal detection systems developed based on deep learning is dominated by CNN. Deep learning implies a neural network with many layers, thus the numbers of the layer in architecture are referred to as the depth of the network. (Karen, 2015) CNN represents feed-forward neural networks which consist of three layers namely, the convolutional layer, the pooling layer, and fully connected layers. (Norouzzadeh *et al.*, 2017) Convolutional layers act as an automatic feature extractor and it produces the feature map. Pooling layers act on the output of the convolutional layer to down sample them. Finally, in the fully connected layer neurons of the input feature maps are linked together with their internal neurons. (Saleh, Hossny and Nahavandi, 2018) To develop a CNN with higher accuracy and less amount of resources transfer learning is used widely. Transfer learning is a method of using previously learned weights in the base classification model as a starting point for current classification models. This reduces training time and resource utilization, providing higher levels of accuracy and reduces the amount of data required. (Willi *et al.*, 2019) In this study, VGG -16 is used as the base model to apply transfer learning. VGG – 16 is one of the best computer vision model architecture. VGG-16 achieved 92.7% top-5 test accuracy on ImageNet, a dataset of over 14 million images from 1000 classes by using only 3×3 convolutional layers stacked on top of each other in increasing depth. Reducing volume size is handled by maxpooling layers of a 2x2 filter. Two fully connected layers, each with 4,096 nodes are then followed by a SoftMax classifier and it contains 1000 channels for each class. (Karen Simonyan, 2015)

B. Animal Prevention

Many animal prevention methods have been existing for different kinds of animals since this study mainly focuses on elephants, wild boar, and buffalo. In Sri Lanka, scream noises, beat drums and trees, cracking whips used to scare away the elephants. (Santiapillai *et al.*, 2010) let bees live in the surrounding area of their field; when elephants try to pass through the barrier, bees will disperse and scream. (King, Douglas-Hamilton and Vollrath, 2007) Moreover, gunfire and firecrackers keep elephants away. Sometimes, pumpkins were filled with poison and explosives and kept them in the field for the elephants to eat. It explodes when it has bitten and blows the elephant's mouth. Throwing boiling oil or burnt polythene onto elephants is also used against the elephant. (Jayantha, 2020) Buffalos normally move with many groups and the target on paddy, corn, mice, and some herbs. There are some methods such as making barriers using magnet tapes, monofilament threads. Commonly buffalos are scared of sudden lights and thunder sounds. (Pandey and Bajracharya, 2016) Apart from that, some of the traditional methods are used such as spraying local pigs' dung solution, burning of dried dung cakes, human hair as a deterrent, erection of used colored sarees, net wires with dense vegetation, planting of thorny bushes, xerophytes around the crop, creation of sound and light through the born fire, local dogs and using traps and poisoning for scaring away wild boars. There are some new methods also applied nowadays, like ultrasound, using guns, and electric fences. (Rao *et al.*, 2015) In general, whilst there are many traditional methods used currently. It is very easy to implement and maintain those traditional ways, as well as that are environmentally friendly. Such as bio fencing, stone fencing, trenches, watchtowers, throwing flaming sticks and rocks, making noises, and unpalatable vegetables are some of them. (Yaw OseiOwusu, 2008; Rao *et al.*, 2015; Pandey and Bajracharya, 2016) The usage of the electric barrier is very efficient, but it harms the animals, and death may occur for animals and humans in this method. (Ahlberg, 2016) Moreover, usage of honeybees'' noise, ultrasound, and sudden flashes are eco (Ecology) -friendly, and cost-effective. (Pandey and Bajracharya, 2016)

Classification Models

A. Data Set

The classification models have been trained using images of elephant, wild boar, buffalo, chipmunk, goat, human, monkey, porcupine, rabbit, and rat. Once necessary images have been collected, images were manually filtered to select the images that only contain animals with a certain level of clarity. In total, 37,387 images were used. Approximately, 6000 images for elephants and 4000 images for each wild boar and buffalo were collected. Images were randomly split into a training set and a validation set to train the model. Out of total images, 80 percentage was used as a training set, and 20 percentage was used as a validation set. In addition to these images, 100 images per each class were collected to test the system.

B. Architecture

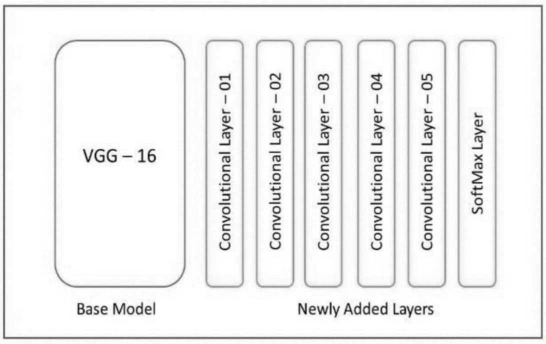

Figure 1: The layout of our CNN classification model

The data set was not large enough to develop a custom CNN classification model to address this transfer learning which has been used to get high accuracy with a small number of images. To implement transfer learning, the VGG-16 classification model was used as the base model. The layers of the classification model are shown in Figure

1. The fully connected layer of VGG 16 has been frozen and five more convolutional layers and a fully connected layer are added to implement transfer learning. Optimization algorithms are responsible for reducing the loss and provide an accurate result. Here, Adam Optimizer was used, which is computationally efficient and works well with a noisy and large amount of data. The model was trained with a learning rate of

0.001 along with 50 epochs and the batch size is 64.

C. Implementation

Two classification models were trained. The Model-1 includes ten-classes that can predict elephant, wild boar, buffalo, chipmunk, goat, human, monkey, porcupine, rabbit, and rat. Model-2 is a three-classes classification model that can predict elephant, wild boar, and buffalo. It was used to increase the confidence of the prediction. The accuracy of the animal detection system has been improved by the combination of Model-1 and Model-2. Initially, the captured image passes through Model-1, and if that is classified as elephant or wild boar or buffalo, then predictions are supposed to choose the particular class. If not, images go through Model-2 then the probability of Model-1 and Model-2 are compared, and the highest value is obtained. The class with the highest probability value is assigned to a particular class. Combining these classification models could improve the accuracy of the model. However, it may increase the misidentification of other animals. Despite the probabilities of misidentification, the model's overall performance will not be affected as the system focuses only on the elephant, wild boar, and buffalo.

Experimental Design

The proposed system contains software and hardware components; therefore, attention is given separately for those two components. In line with that, the software component has two main functions: animal detection and alerting the user. The hardware section has two main functions: implement an image capturing process and scare-away mechanism processes. The overall idea of the system will be implemented and follow the process as shown in Figure 2. The infrared thermometer continuously reads the temperature of the environment within its range. It will be triggered by a temperature greater than or equal to 35^{0}C. Then, the trigger is sent to the Raspberry Pi to capture the image and classify the image using the classification model. If that image is classified as elephant or buffalo or wild boar, an appropriate scare-away mechanism will be implemented to scare them away and the user will be alerted.

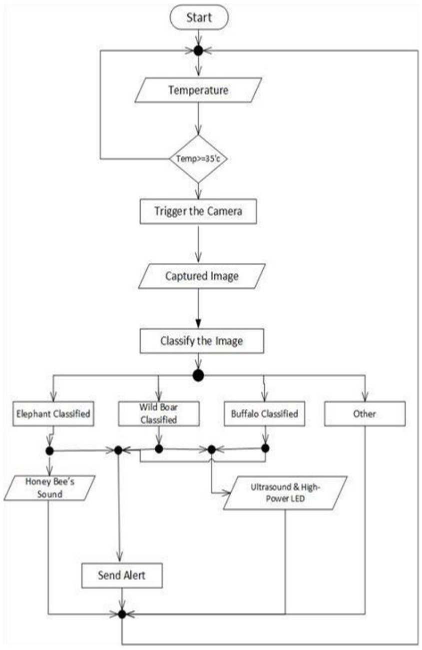

Figure 2: Flow chart of the system

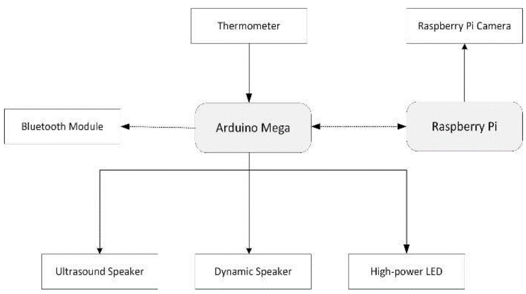

Figure 3: Hardware Components of the system

A. Hardware Components

The whole system is built with two separate hardware components using the Raspberry Pi 3 Model B and the Arduino Mega 2560 R3 Board. The components of the temperature sensing mechanism and scare-away mechanism are connected to the Arduino, and the Raspberry Pi serves as a processing unit for detecting animals and used to the image capturing process. Both boards communicate with each other wirelessly via using Bluetooth technologies. Figure 3 shows how components are connected to the Arduino Mega and Raspberry Pi. MLX960614 Infrared Thermometer, HC-05 Bluetooth

Module, Dynamic Speaker, Ultrasound Speaker, HighPower LED (Light Emitting Diode), and DFPlayer Mini were connected to Arduino Mega. Baud rate of 9600 bits/second is used to communicate with these components.

The Raspberry Pi camera module V2 is connected via the CSI (Camera Serial Interface) of Raspberry Pi. The MLX960614 infrared thermometer used to read the temperature of the environment and the body temperature of the animal. The HC-05 Bluetooth module can add twoway (full-duplex) wireless functionality. It has a transmission range of up to 10 m. Raspberry Pi Camera Module V2 is a high-quality 8-megapixel camera that can capture images of 3280 x 2464 pixels. Dynamic speaker, ultrasound speaker, high-power LED, and DFPlayer Mini used for scare-away mechanisms.

B. Image Capturing Process

The image capturing mechanism involves two hardware components, which are an infrared thermometer and a Raspberry pi camera. The infrared thermometer senses the temperature greater than or equal to 35^0C, it sends a trigger to the camera to capture the image. 35^0C was selected as the triggering temperature. The infrared thermometer reads the temperature almost every second, and when it reads a temperature higher than or equal to 35^0C, it sends the raspberry upward trigger within 2 seconds. Once the trigger has been received, Raspberry Pi will capture the image. The captured image is saved as a jpeg (Joint Photographic Experts Group) format in the root folder of Raspberry Pi. An existing image will be replaced once a new image is captured.

C. Scare-away Mechanism

The following scare away mechanisms were identified since this study focuses on buffalos, wild boars, and elephants. The elephants can be frightened by the noise of bees, buffalos and wild boars can be frightened by sudden high beams of light and ultrasound. If an animal is classified as a wild boar or buffalo or elephant, the appropriate scare-away mechanism is applied for about 10 seconds after classification. If the elephant is detected, the dynamic speaker will emit the sound of honeybees, as well as if the wild boar or buffalo detects the ultrasound, and the sudden light emitted by the ultrasound speaker and highpower LED. The prediction result can be obtained from the Raspberry Pi to the Arduino via Bluetooth interconnection within one second after prediction and the scare-away mechanism starts working at the next second. The highpower LED emits, sudden flashes at a frequency of 15 Hz, and ultrasound emitted at 35000Hz.

D. Alert the User

An Android mobile application was developed using node.js to receive alerts from the system and let the user know about the detected animal. A single column real-time database was created with a firebase. The Firebase Realtime Database is a cloud-hosted, store, and sync data between users in real-time and developed by Google.

Whenever the animal is detected the predicted animal's details are sent to the firebase database and stored, by retrieving the stored information via the mobile application user can know which animal is predicted.

Result and Discussion

The findings are based on manual testing. Initially, the system was separately tested by each objective then, the whole system was manually tested by triggering the infrared thermometer with human body temperature. In order to test, an image of the animal was placed in front of the camera. Once the animal's image was captured, it was classified. After the classification, the scare-away mechanism was successfully implemented. Meantime, the prediction result uploaded in the real-time database alerted the user.

A. Image Capturing Process

The effectiveness of the image capturing was assessed based on the infrared thermometer's capacity to senses the body temperature and triggering the process to capture the images. In every attempt, an infrared thermometer senses the body temperature when it was equal or greater than 350C and the camera was triggered. It was observed that once the triggers were received the camera captured the images without any failures. According to the findings, the sensor tracked the animal's body temperature every second whenever an animal enters the region. Significantly, the system captured the image within 2 seconds after detecting the body temperature of the animal. Moreover, the python script effectively loaded and predicted the animal every time an image was captured.

B. Animal Detection Process

Hundred images were collected for each class and validated the classification model. A classification model was tested and evaluated at the level of prediction by testing each image to our classification model. The combination of two classification models detected elephants, buffalos, and wild boars with an average accuracy of seventy-seven percentage. Figure 4 shows the numbers of true positive predictions out of 100 images of each class animal. This model successfully detected 64 images of the wild boar, 78 images of the buffalo, and 89 images of the elephant out of 100 images of each animal. Most images were predicted as true-positive even though few of them were obtained as true-negative. The Model-1 includes ten-classes with an average accuracy of 68.80%. The Model-2 is a threeclasses with an average accuracy of 68.33%. Figure 5 shows the numbers of true positive predictions out of a hundred images of animals in each class of both model-1 model-2. This shows that the prediction was improved in the combined classification model. Numbers of true positive prediction of wild boar in model-1 and model - 2 is 41 and 54 respectively, it was improved to 64 in the combined model. Similarly, the true prediction of buffalo was improved to 78 from 62, and for elephants, it was improved to 89 from 85.

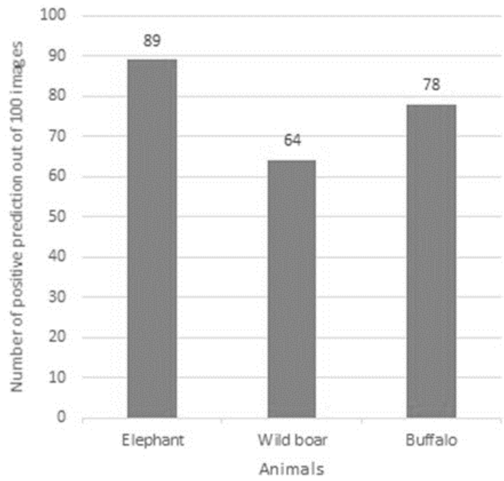

Figure 4: The number of true positive predictions out of 100 images for each class in the combined model

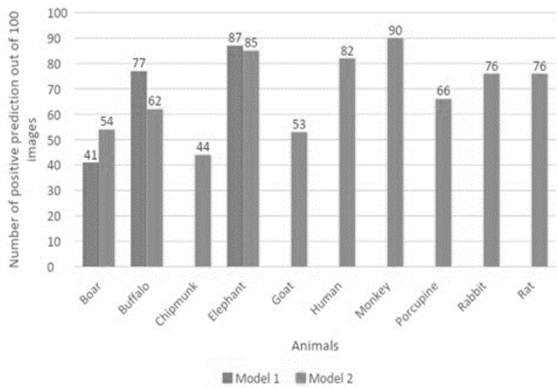

Figure 5: Number true positive prediction out of 100 images in Model-1 and Model-2

C. Scare-away Mechanism

The necessary inputs were manually given to test the scare away mechanism. The system successfully understood the input and produced an appropriate scare-away mechanism. A scare-away mechanism was implemented for 10 seconds after the trigger of an appropriate scare-away mechanism was activated based on the detected animal. As per our testing, the scare away mechanism worked very well every time according to the prediction.

D. Alert the User

The system was built to send an alert to anyone who installed the mobile application. An alert was sent to the user's mobile application as soon as an animal was detected. At the instance of the detection of animals, information is saved into the firebase's real-time database. Figure 6 shows the screenshot of the alert messages when an elephant, buffalo, and wild boar were detected. We found that the user received the alert in real-time and effectively as a result of the internet based alert system. Since the system was based on the internet, the ability to receive an alert was not affected by the distance between the system and the user. However, the performance of the mobile application could vary based on the availability of the internet.

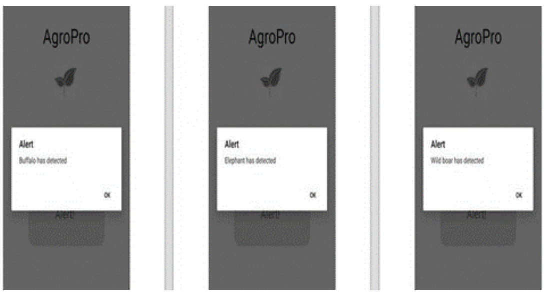

Figure 6: Screenshot of user alerts

Conclusion and Future Works

A large number of human-animal conflicts have been reported in the past, causing serious damage to the crop, downturn the economy, and mishap the lives of farmers and animals. With this background, there is a need to protect the crops from the animals, and to avoid harming the animals. The system was proposed to address human and animal conflict. A real-time deep learning-based system was suggested for animal detection and prevention of human-animal conflicts in crop field areas. The system was developed to automatically detect and scare away elephants, buffalos, and wild boars. The system has been implemented to achieve three objectives: detecting animals, preventing animals from entering the field, and alerting the user. Briefly, when an animal with a temperature above 350C entered the area where the infrared thermometer was placed, it sent a trigger to the camera. According to the trigger of the infrared thermometer, the camera took a picture of the animal. Once the picture was taken, the captured image was sent to the classification model to predict the animal. The output of the classification model implemented a relevant scare away mechanism, for example, a bee buzzing sound, ultrasound, or sudden flash of lights. At the same time, Details of the animals will be sent to the farmer through the mobile application. Our findings indicated that the detection system provided an average accuracy of 77%. It took approximately 40 seconds from sensing the temperature to a scare-away mechanism. The accuracy of the model can be affected by the amount of data that we have used. In this case, the number of images and the number of epochs may not sufficient enough. Along with that, the transfer learning approach may lead to overfitting, specifically, in the transfer learning method any pooling layer wasn't added, which also leads to overfitting.

Some advanced features can be added to improve the system and derive a better performance. Here, the accuracy of the current model can be increased by adding more layers and increase the number of epoch and the amount of dataset. Along with that, other architecture like resnet50, GoogleNet, and others can be used as a base model, which may perform more accurately.

Animal detection accuracy and numbers of animals can be improved using pre-trained APIs to reduce the limitations of the system. The efficiency of the thermometer could increase by alternating higher range sensing thermometers. It will be better to use a large number of cameras and sensors to acquire more efficiency and accuracy of the whole system. Moreover, by inserting a SIM (subscriber identity module) module, the system can send text messages whenever the internet becomes unavailable. In the future, a revised version of the system can be applied to address other human-animal conflicts. It could be modified to scare away other animals such as monkeys, porcupines, insects, and birds. Apart from this, it can be modified to protect villages and homes from wild animals by alarming and scaring away them before they enter the boundaries. Significantly, a modified version of the system can be used to alert drivers about animal crossing areas of major roads and railway crossings. The driver could be alerted about the presence of certain animals and ensure pedestrian safety. It can reduce road accidents caused by animals.

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