Transition from Observation To Knowledge To Intelligence (TOKI)

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An Intelligent Bird Scaring System for Cereal Farms

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Abstract. Machine learning is a field of study whose application is gaining prominence in solving problems in an automated and effective way in many sectors, agriculture not excluded. In Nigeria to date, bird scaring in the agricultural sector, is effected manually, by the use of human scarers who scare birds away from farms. The aim of this work is to present an alternative approach to solving the bird scare problem by proposing an intelligent bird recognition system that can simulate sounds to scare birds, in cereal farms. Several videos containing birds were fetched from the internet to test the system. A pre-trained convolutional neural network model, Single-Shot Multibox Detector with Mobilenet from the TensorFlow object detection API was used in deploying a bird recognition system to a Raspberry Pi 3 device. The system through a camera attached to a Raspberry Pi, streams and processes real-time video frames from the farm. On detection of a bird in a video frame, the bird-recognition system would generate bird distress call sound. Evaluation metrics used to evaluate the system include Frame Rate, Recall, Inference time and reliability of sound generation. The results indicate that the Recall value is 62.5% for any single image frame. The frame rate of the processing pipeline was 0.78 while the inference time for detection is 877.384ms. The system reliably generated sound on every detection of bird in any image frame and the sound automatically stopped when there was no bird in view.

Keywords: Raspberry Pi, Object Detection, TensorFlow, Bird Scaring.

1. Introduction

The rise in artificial intelligence, machine learning and portable computing devices over the last few years put us at a great feat to solving problems in an automated and effective way. The Raspberry Pi is a portable device revolutionizing how to automate tasks originally done by humans. Remarkably, the device which is a small single-board computer, was originally developed to support the teaching of computer science in schools. However, the device became so popular that it was useful even in the field of robotics. In this work, we present yet another alternative and productive use of the Raspberry Pi. The alternative approach presented herein will leverage deep convolutional neural network – a field of machine learning that has made remarkable progress on addressing hard visual recognition tasks which matches or exceeds human performance in some areas. (https://tensorflow.org)

According to Clarke (2004), birds are the leading pests that cause damage to produce in farms and orchards. Consequently, they destroy farm crops, causing farmers to lose considerable amount of money. A great percentage of the farmers surveyed by Coleman (2001) at the New Zealand Plant Protection Society had encountered crop damage due to bird infestation. In some cases, the extent of the damage was as high as twenty percent of the farmers' total harvest for that year. A review carried out in different parts of Nigeria at diverse periods, also showed that farmers perceived birds as the major pests in rice production (Elliott & Bright, 2007, and Bright *et al*, 2009). In some areas covered in the review, the reviewers noted that around 75% of the total farm produce could be destroyed by birds while half of the production costs went into bird scaring. A large majority of the farmers in the study indicated that human scarers were their main approach to bird scaring.

Despite the importance of cereal produce to the economy of Nigeria, in the agricultural sector manual labour still predominates the bird scaring operations (Augustine, 2012). The manual approach is the use of human scarers, farm workers who scare birds away. This approach is very exhausting, time-consuming and often expensive. Another approach is exclusion netting or the use of scarecrows. However, birds become habituated to these approaches quickly, therefore, they provide protection for a brief period. In spite of the aforementioned practices, birds still cause huge losses to cereal farmers in Africa. The Global Rice Science Partnership in 2010, identified birds as the second most significant biotic constraint in African rice production, next to weeds (IRRI., 2010). Birds become a problem from the ripening phase until harvest.

The unavailability of an intelligent and efficient approach to control bird damages on cereal farms has been a major issue and has contributed to low yields at the end of harvest. Farmers also want to reduce recurring wages paid to human scarers on cereals farms in order to maximize profit. In this work, we propose an alternative approach to solving the bird scare problem in cereal farms especially rice farms; by offering an intelligent bird scaring system which upon recognition of a bird in sight, will play distress call sound to scare birds away.

2. Related Works

There are several approaches used to achieve bird control or deterrent in farming and Bishop *et al* (2003) wrote a good summary about them. The approaches could be physical, visual, multi-sensory, audio or chemical in nature, to mention a few. Each of these methods or approaches has its own problems or limitations. A few of them are mentioned herein.

Bio-acoustic devices are the usual choice in bird control and according to Bishop *et al* (2003), the bio-acoustic devices transmit naturally occurring sounds like bird distress calls to deter birds, although they noted that some of the calls are responded to by specific bird species. Some of the devices are said to produce noise levels around 110dB with an operative distance of 300 metres. The Bird Chaser (fig 1), an example of a bio-acoustic system, is activated by motion via a sensor after which it transmits its sound. Unfortunately, bio-acoustic systems lose their efficiency if they are not moved around periodically and as such, they are best used in combination with a number of other techniques.

Another method of bird scaring is the use of non-lethal, environmentally safe methods such as lasers (fig 2) that offer low power levels, accuracy and distance. Laser devices work under low light situations (Bishop *et al*, 2003) and are silent in nature, thereby making them an attractive option over bio-acoustic devices. Birds are not likely to get accustomed to the laser beams and as noted by Blackwell *et al* (2002) the Class III B laser, which have a power rating between 5mW and 500mW are classified as safe to use by the United States Department of Agriculture. This class of lasers are usually incapable of producing harmful diffusion except they are directly pointed at the human eye.

Figure 1: Bird Chaser (www.pest-control.bz)

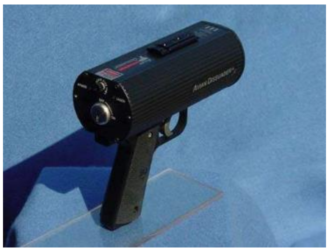

Figure 2: Avian Dissuader (SEA Tech Website)

Although the use of laser devices as bird scarers can be effective, the equipment is expensive. Besides, the users need to be specially trained and safety precautions observed in order to achieve thorough bird deterring. In addition to that, the laser approach to bird control is only feasible as night because their effectiveness decreases as light levels increase. Unfortunately, in Nigeria, human scarers remain the most used method of bird control in most cereal farms (Bright et al, 2009), despite its cost.

3. The Proposed System

The proposed system is a mobile, portable and self-contained platform and as such uses a Raspberry Pi 3 Model B device. To develop the intelligent bird scaring system, several resources such as OpenCV's Deep Neural Network (DNN) library, TensorFlow object detection API and other third party libraries were utilised. TensorFlow object detection API offers many great pre-trained models for object detection that reaches high accuracy in detecting various objects from humans, cars, birds among others.

3.1. Raspberry Pi 3

The Raspberry Pi is a single-board Linux-based computer, with its microprocessor, wireless radios, memory and ports integrated on one circuit board. It does not have a built-in hard drive or storage location, consequently the Raspberry Pi’s operating system is usually installed onto a microSD card, where all other files including programs are stored. The board also includes wireless LAN and Bluetooth Low Energy for communication, as well as peripheral ports. The device is powered via 5V micro-USB connection. It is recommended to have a 2.5A power supply. Due to the low computational power of Raspberry Pi, it is quite tasking and hard to run a deep learning algorithm on it, therefore OpenCV DNN libraries were employed.

3.2 Open Source Computer Vision Library (OpenCV)

The OpenCV DNN module runs much faster than other libraries (SATYA, 2018), and conveniently, it only needs OpenCV in the environment (on the Raspberry Pi). The best use of OpenCV DNN is performing real-time object detection. This process can run in any environment where OpenCV can be installed and does not depend on the hassle of installing deep learning libraries with GPU support. OpenCV DNN supports models trained from various frameworks like Caffe and TensorFlow. It also supports various network architectures based on, MobileNet- SSD (the model being used), Inception-SSD, Faster-RCNN Inception, Faster-RCNN ResNet, and Mask-RCNN Inception. The OpenCV 4.0.1 module was compiled from source and installed on the Raspberry Pi after which it was used to run the model.

3.3 TensorFlow Object Detection API

TensorFlow object detection API is a very powerful open source framework, with the aim of making it easy for researchers to construct, train and deploy object detection models. This tool enables anyone to quickly build and deploy powerful image processing software. Google has a collection with pre-trained object detection models that have various levels of processing speed and accuracy. The Raspberry Pi has a weak processor and limited RAM. For this reason, a model that takes less processing power is needed. The SSD (Single Shot MultiBox Detector) model works fast and requires less computational power as compared to the other model (Huang, *et al* 2017). Based on this, the SSD model with Mobilenet v2 was chosen.

3.4 Bird Distress Call Audio files

To deter birds using sound in large open fields, certain bird distress calls are transmitted. These are recorded bird-distress calls that are usually played back along with predator bird calls. The natural instinct of birds is to flee the area when the bird hears these sounds. For this work, bird sound deterrents as audio files were extracted from a video of bird distress call obtained from Absolute bird control products website (Absolute bird control, 2018). These files were added as part of Intelligent Bird Scaring System and played back when necessary.

3.5 The Intelligent Bird Scaring System (IBSS) setup

As stated earlier, this work was developed to proffer an alternative approach to manual bird scaring in cereal farms. The IBSS is made up of a hardware device with several modules deployed to it. Since it is expected that the cereal farms will be scanned in real-time, we used a Raspberry Pi as described above with a Raspberry Pi Camera V2 attached to it as shown in figure 3. This was later covered in its housing. Furthermore, a speaker was connected to the 3.5mm 4-pole composite video and audio output jack of the Raspberry Pi to play the random distress sound generated when a bird is detected in a video feed.

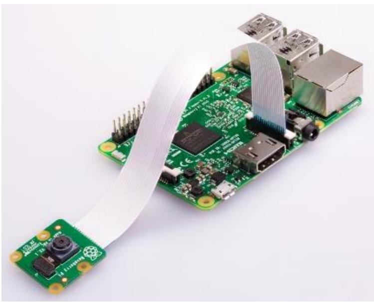

Figure. 3. A Raspberry Pi with Pi camera V2 attached (Source: Upton, E. (2018)

In this study, the Raspberry Pi was accessed through a Secure Shell (SSH), since the device does not come with a display monitor, keyboard or even a mouse. This means accessing the command line of the Raspberry Pi remotely from a computer or device on the same network using SSH. For this, an Ethernet cable was used to establish a wired connection from a computer to the Raspberry Pi. As soon as the connection was established, the Raspberry Pi was accessed through its IP address on the network and a python program was saved on the memory card of the device. Prior to feeding the image frames to the object-detection module, the image frame was converted to a blob. A blob is a pre-processed image that serves as the input to the module. The image frame in blob format was then fed to the model for detection. When IBSS is activated, anytime it detects a bird in an image frame to a certain degree of confidence, distress bird sound would be triggered and played via the speakers attached to the Raspberry Pi device. As soon as image frames with no birds appear, the sound ceases. Our system was deployed and tested on a Raspberry Pi with the following specifications: RAM – 1 GB, Processor: 4 × ARM Cortex-A53, Clock speed: 1.2GHz. Several video files were obtained from the Internet to test the intelligent bird scarer. These files ranged from 10 minutes to 25 minutes in playback length and they were all in mp4 format. The video files contained frames that had birds and some frames that had no birds.

The deployed detection model was subjected to some evaluation to measure its performance. 50 image frames were extracted from the evaluation data to estimate reliability of detection, inference time and reliability of sound generation. Each image frame was captured after every 600 frames in the evaluation data. A sample video (about 1 minute) was extracted from the dataset and was used to determine the Frame Rate and Reliability of Detection.

4. Results

Figure 4 shows an image frame from the evaluation data that shows detected birds. The bird detection model was subjected to the evaluation data and the bird distress call sound was played automatically by the system when birds were in view of the camera and the sound paused when the birds were out of view of the camera.

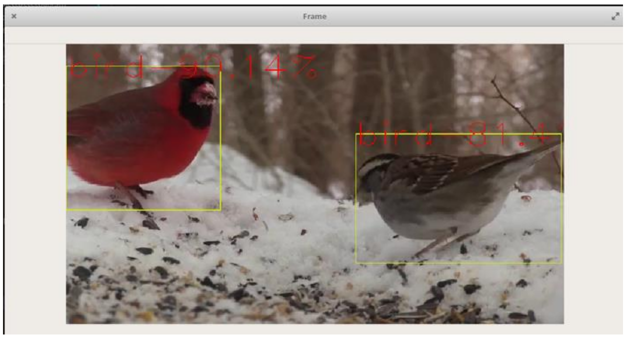

Figure 4. Image frame with birds detected

Figure 5 on the other hand shows image frames where some birds in the image were not detected. It was observed that the bird detection model did not work well with very small birds as well as birds whose distance were far from the camera view. This is expected as the SSD Mobilenet Model used in this work is known to be less accurate with small objects; therefore, for an application where speed is not the most essential consideration, Faster R-CNN model could provide better accuracy for small objects (Huang *et al*, 2017).

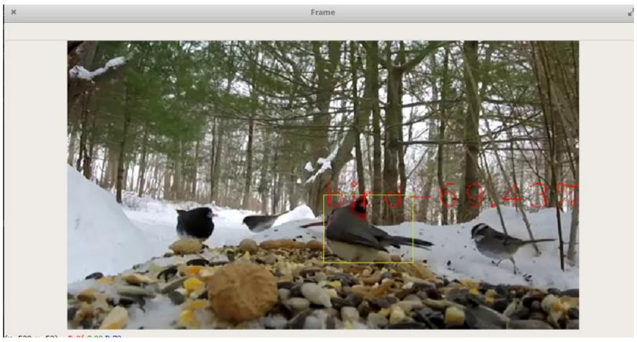

Figure 5: Image frame with some birds not detected

Table 1: Frame rate from review of detection results.

No of frames Processed	Total time taken (sec)	Frame Per second (FPS)
2400	3065.7	0.78

The frame rate of the processing pipeline when the model is deployed to the Raspberry is at **0.78 FPS**. This performance can be attributed to the low processing power of the Raspberry Pi and its limited RAM size (1GB).

Table 2: Inference time from review of detection results

Total Inference Time (ms)	No. of frames	Average Inference Time (ms)
43869.212	50	877.384

The SSDlite Mobilenet model used for the object detection has its standard speed of detection (inference) at 27 milliseconds (Rathod and Wu, 2017) however, from the result that was obtained (table 2), the speed of inference performance of the bird detection model on the Raspberry Pi was 877.384 milliseconds. This is largely due to the low computational power of the Raspberry Pi.

Table 3: Recall from review of detection results

Total True Positive	Total False Negative	Recall
40	24	0.625

The Recall metric is a measure of percentage of relevant objects that are detected with the detector. 50 frames were used to obtain the recall result. The recall rate was 62.5%. The reliability of bird distress call sound generation entirely depends on recall metric as every time the model predicts accurately, the bird distress call sound is also generated and stopped automatically when no bird is detected.

4.1 Cost of the proposed system

The total cost of the hardware devices used is stated the table 4. Since it is a one-off purchase, it thus reduces the cost of bird scaring in farms in the long run.

Table 4: Cost Analysis of the device

S/N	Item	Unit Cost (₦)	Quantity	Amount(₦)
1	Raspberry Pi	20,000.00	1	20,000.00
2	2 Pi Camera	9,200.00	2	18,400.00
3	Solar Battery	3,600.00	1	3,600.00
4	Speaker	3,000.00	1	3,000.00
5	Heat sink/Fan	5,000.00	1	5,000.00
			Total	**50,000.00**

4.2 Prototype of the proposed device

The final design of the proposed device is as shown in figure 6.

Figure 6: Prototype of the proposed device

5. Conclusion

An SSD – Mobilenet object detection model was deployed and tested for bird recognition on a Raspberry Pi 3. The level of reliability achieved by the system is reasonably fine given that the system is real-time and that the hardware device used has low computational power.

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