

K'eyema-ba: Pest Detection and Prevention using Unmanned Aerial Vehicle on Farmland

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Case Studies at SciTinyML Workshop

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INTRODUCTION

- The area of land farmed in Africa is predicted to double by the year 2050 yet very few African studies have investigated the impact of different farming intensities and regimes on bird communities

The Density and Diversity of Birds on Farmland in West Africa. Available from:

https://www.researchgate.net/publication/242685697_The_Density_and_Diversity_of_Birds_on_Farmland_in_West_Africa [accessed Jul 29 2020].

- World bird damage problems are numerous, costly, and varied, but often similar from continent to continent.
- In Nigeria, bird scaring in the agricultural sector, is to date effected manually
- The need for a disruptive technology to change the narrative is imperative if agricultural production rate will increase on the continent of Africa



IMPLICATIONS

- As farm produce gets higher, the threat of bird damage on crop increases
- Damaged fruits will attract insects, and contribute to spreading diseases
- Profit degradation sets in
- Food shortage
- Bird control is important as birds can create health-related problems through their droppings
- Farmers have always been adopting manual precautionary approach
- The need for automated bird scaring system



LITERATURES

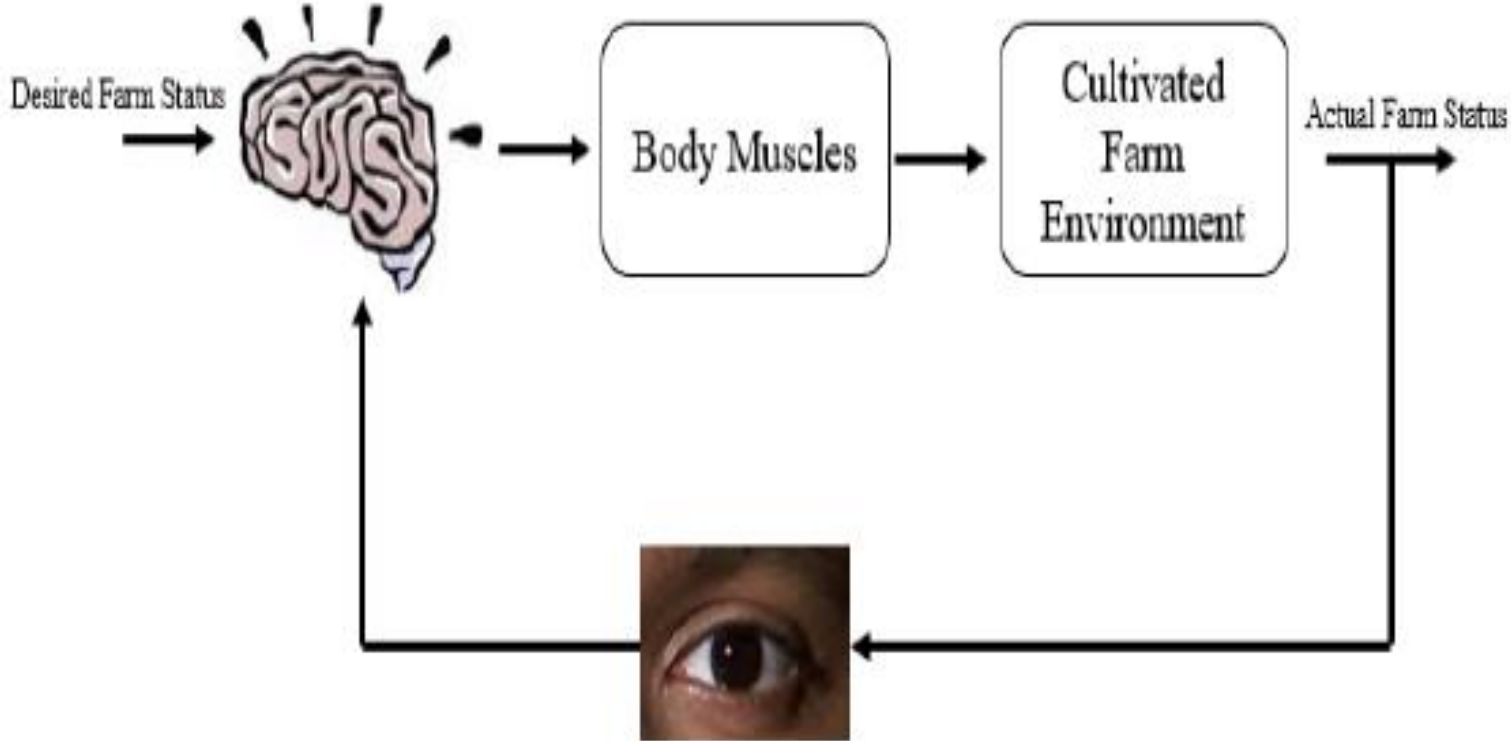
| AUTHOR | YEAR | WORK DONE |
|--------------------------------|------|---|
| Bomford and O’Brirn | 1990 | Estimated that US fruit growers lose hundreds of millions of dollars every year due bird damage and also in expenditures to mitigate those damages, as fruits ripen, a number of birds attracted to the fruits will rise exponentially |
| Amaefule, Ezeonue, and Okonkwo | 2015 | Asserted that Several devices have been used to control the menace of birds both at the airports and farms but the use of electronic scarecrows is a relatively new invention |
| Bhatt, Patel, & Sharma | | A survey of different animal object”, detection techniques such as object matching, edge-based matching, skeleton extraction etc. was carried out. After survey, the most appropriate method is selected for animal detection and efficiency is measured. |
| Adebayo, <i>et.al</i> | 2016 | worked on increasing agricultural productivity in Nigeria using wireless sensor network. The system is able to sense environmental parameters and transmit findings to the base station in order for a farmer to make decisions such as to actuate irrigation scheduling, fertilization scheduling etc, the sensors are uniformly distributed and used for nodes localization |
| Abed | 2018 | Made use of CamShift (Continuously Adaptive Mean Shift) algorithm and color detection in darkness for tracking a target with video sequences in real time. The system described in this paper contains a camera that is connected to a Raspberry Pi. |
| Wang, <i>et. Al</i> | 2015 | Reviewed deep learning algorithms applied to video analytics of smart city in terms of different research topics that cut across object detection, object tracking, face recognition, image classification and scene labelling. |
| Wang, <i>et.al</i> | 2016 | Presented a visual object detector based on a deep convolutional neural network that quickly outputs bounding box hypotheses without a separate proposal generation stage. The network was modified for better performance and thereafter specialized it for a robotic application involving birds and nest categories. The system exhibited very competitive detection accuracy and speed as well as robust, high speed tracking on several difficult sequences. |

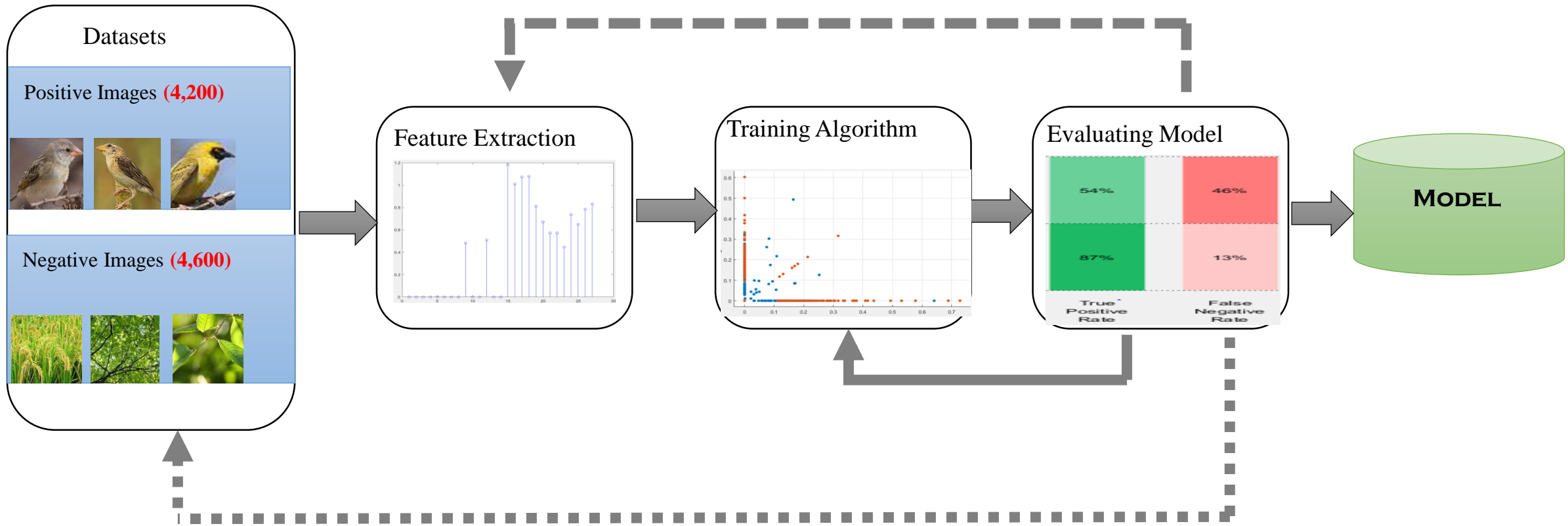


Popular Bird Scarecrows on Most Nigerian Farms



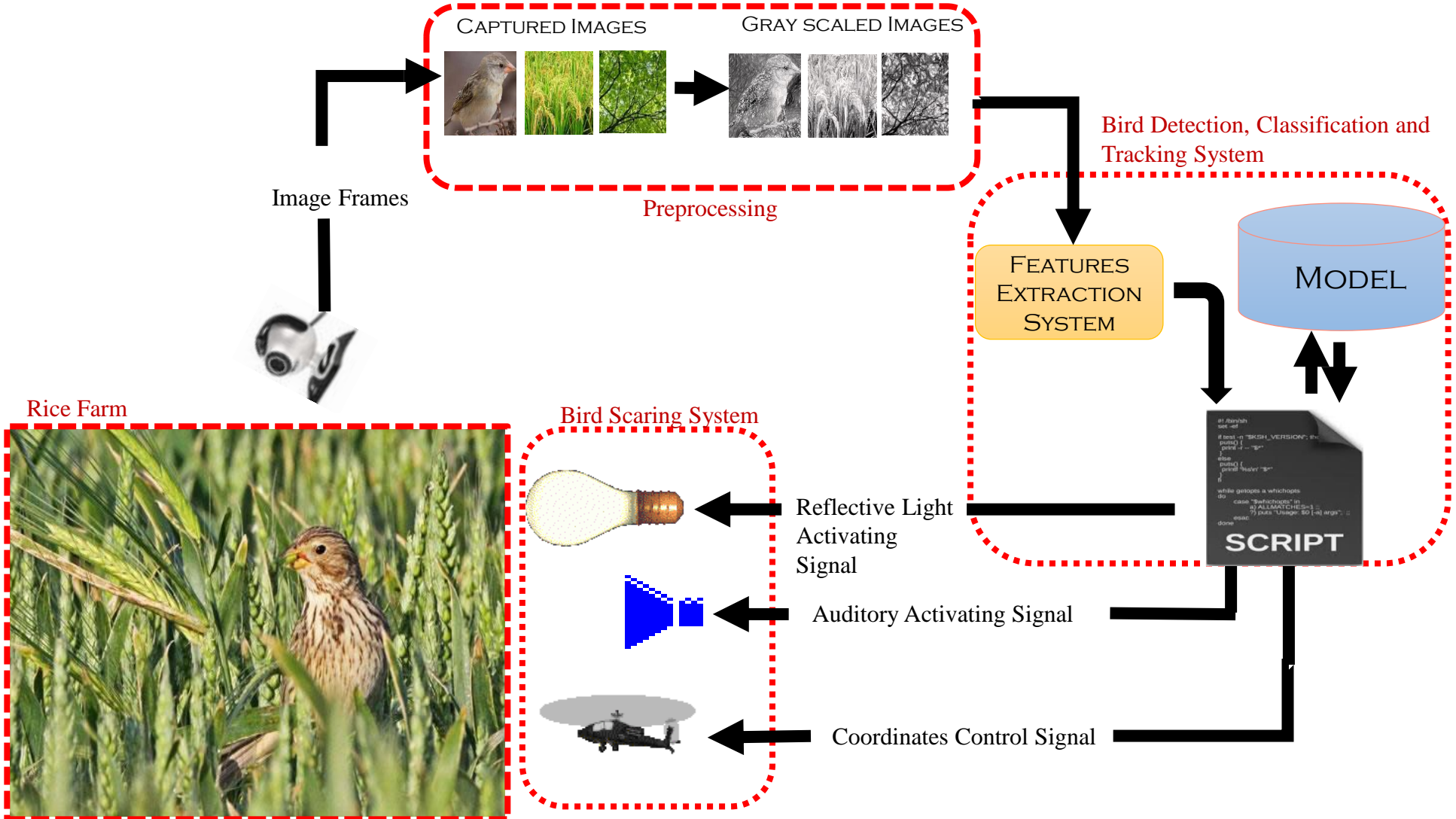
EXISTING FARM PROTECTION CONCEPT



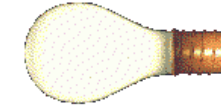
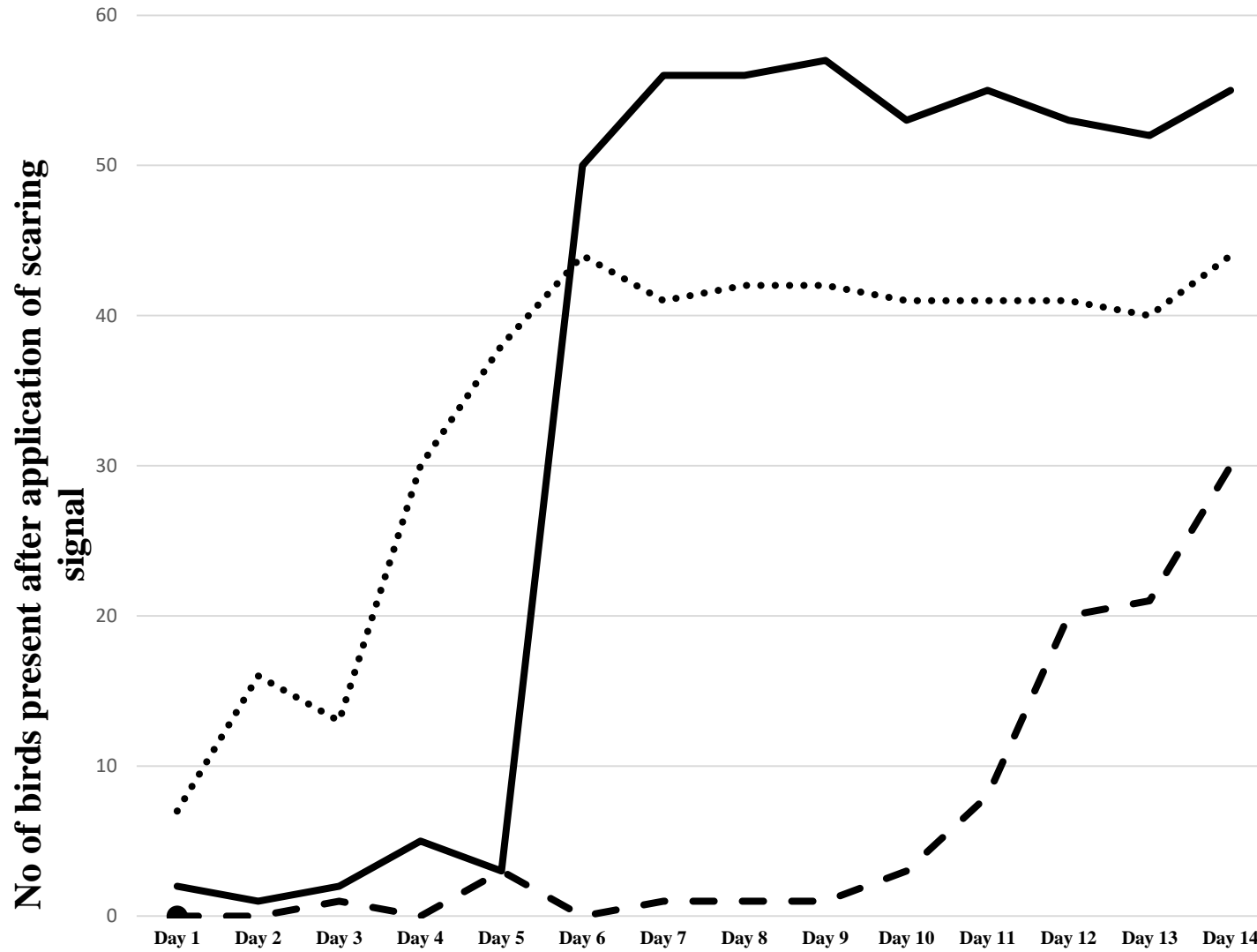


- Features of the desired birds to be detected were extracted and labelled as positive images while that of surroundings and other images labelled as negative images.
- Extracted Features are: Haar-like, Local Binary Pattern (LBP), Histogram of Gradient (HOG)
- Algorithms: Retinanet, Yolo v3 and Faster-RCNN

CONCEPTUAL DESIGN



PRELIMINARY RESULT

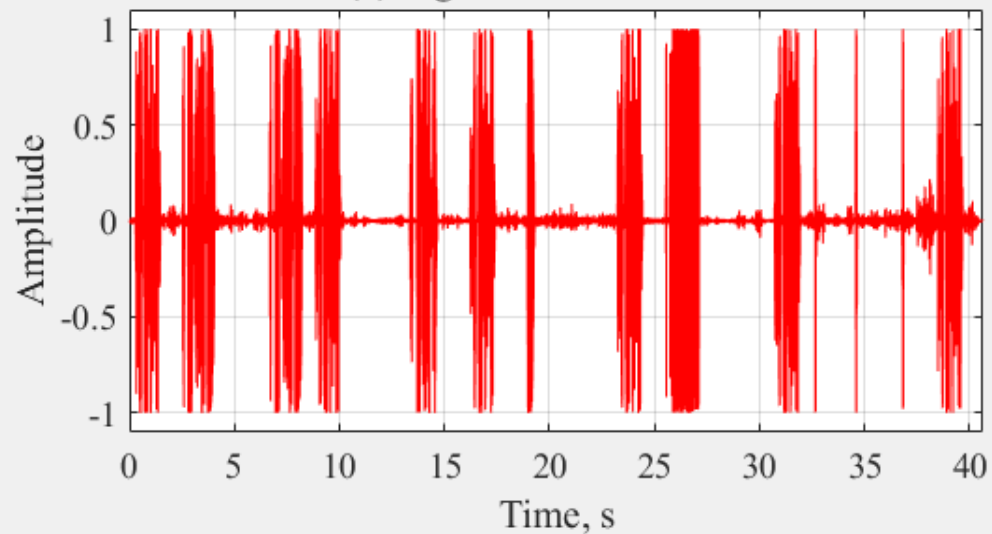


- Light
- - - Distress call
- Prdator's call

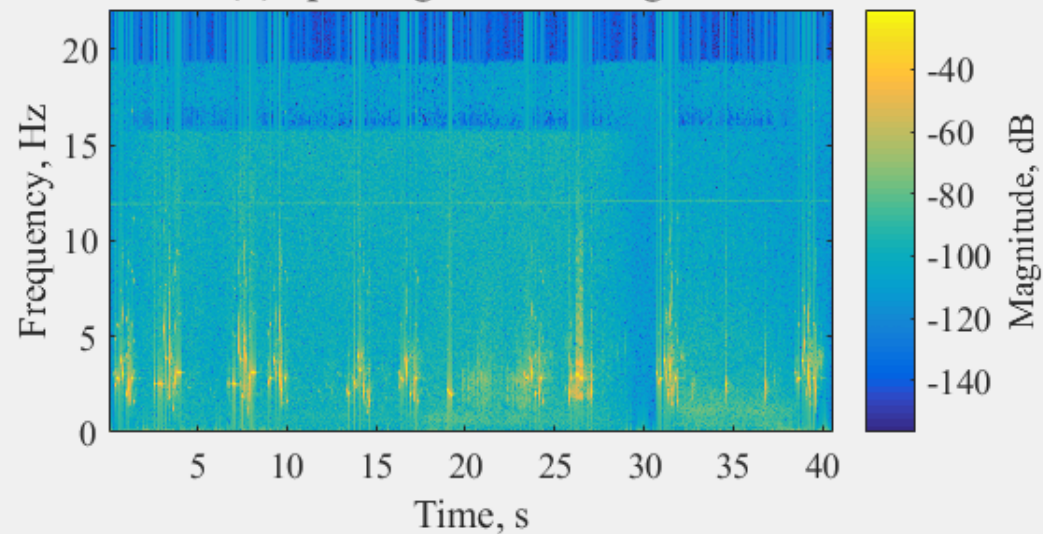


PRELIMINARY RESULT

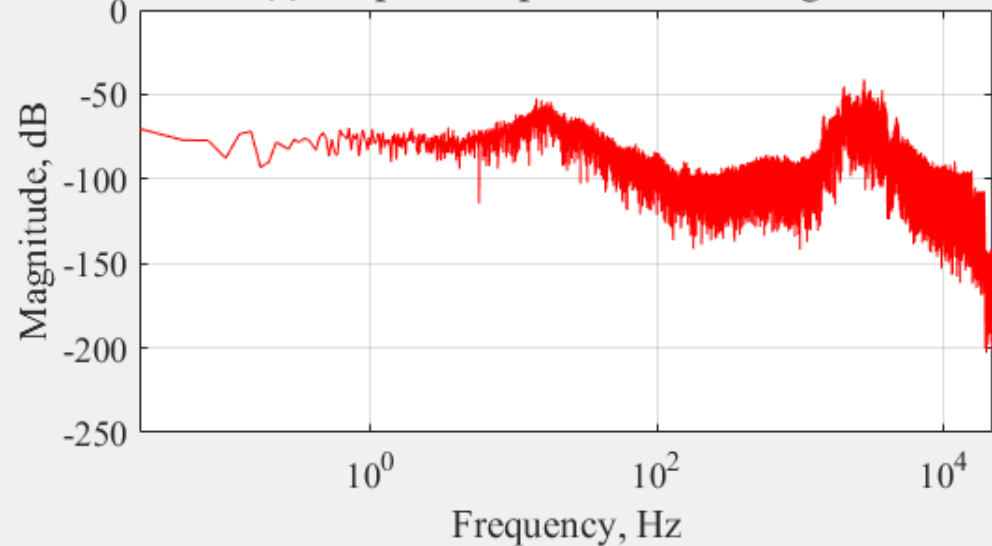
(a) Signal in time domain



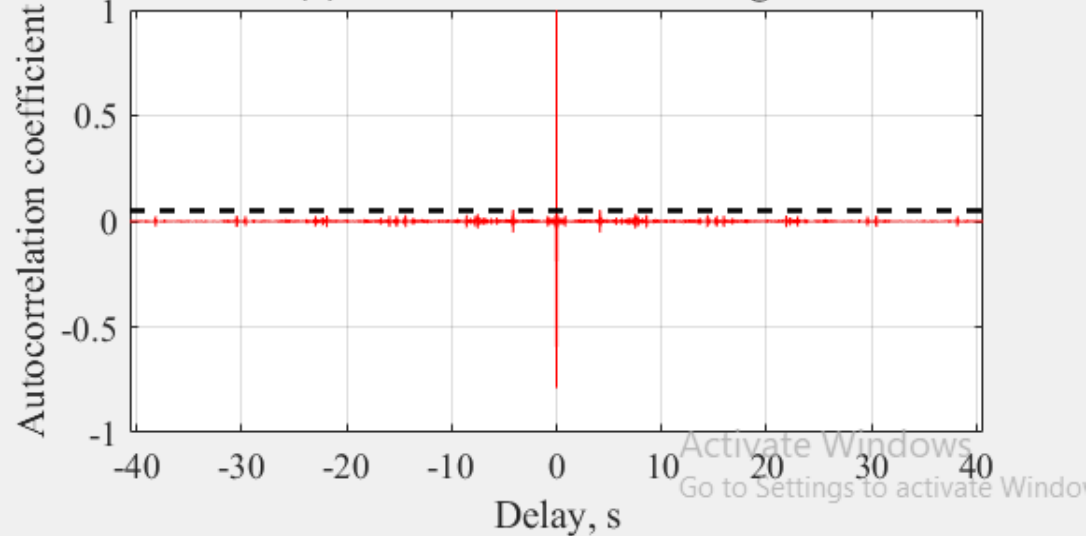
(b) Spectrogram of the signal



(c) Amplitude spectrum of the signal



(d) Autocorrelation of the signal



PRELIMINARY RESULT

RECOGNITION TIME

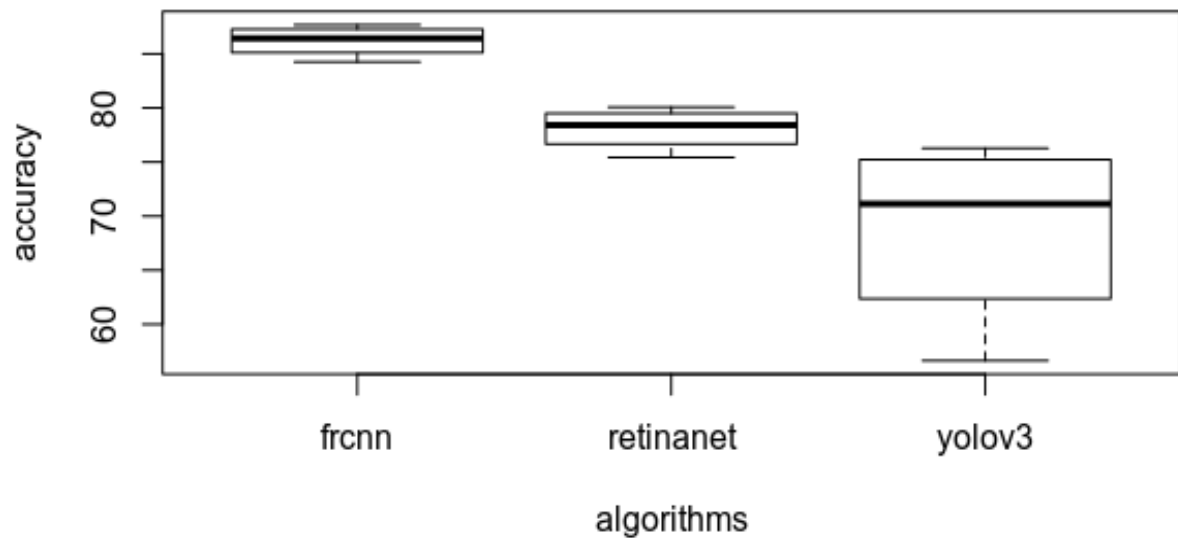
| THRESHOLD | RETINANET (s) | YOLOV3 (s) | F-RCNN (s) |
|-----------|---------------|------------|------------|
| 0.20 | 2286.87 | 165 | 3646.21 |
| 0.30 | 2361.47 | 178 | 3741.46 |
| 0.40 | 2347.42 | 168 | 3523.39 |
| 0.50 | 2357.99 | 167 | 3745.26 |

Accuracy

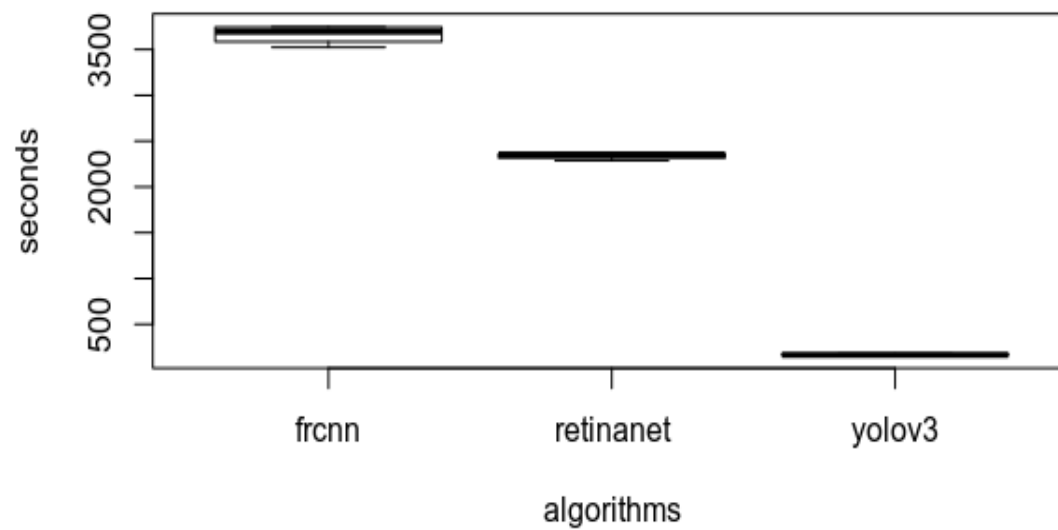
| THRESHOLD | RETINANET (%) | YOLOV3 (%) | F-RCNN (%) |
|-----------|---------------|------------|------------|
| 0.20 | 80.07 | 76.27 | 87.68 |
| 0.30 | 78.93 | 74.18 | 86.88 |
| 0.40 | 77.89 | 68.09 | 85.97 |
| 0.50 | 75.43 | 56.64 | 84.25 |

PRELIMINARY RESULT

- Analysis of variance (ANOVA) was carried out to validate the results obtained and the graphs are as shown

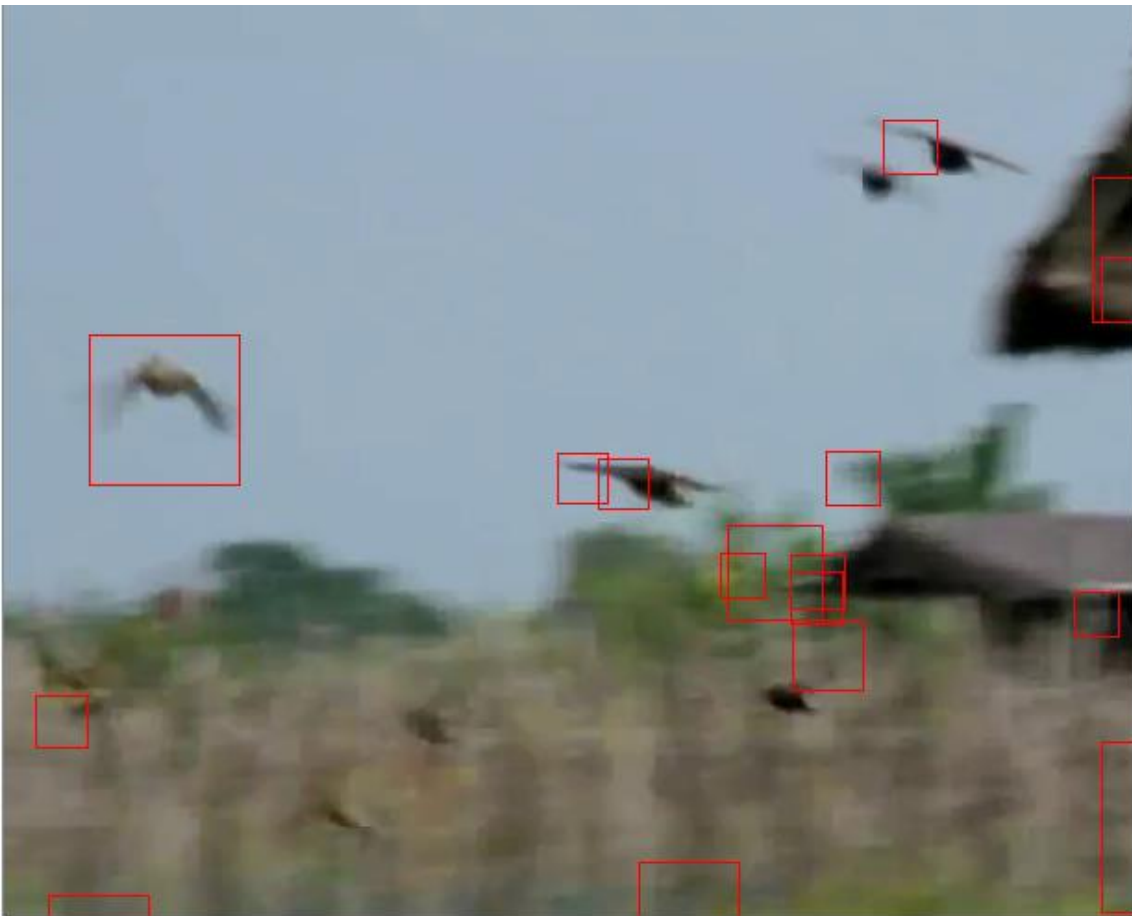


Accuracy



Recognition Accuracy

PRELIMINARY RESULT



```
RESTART: C:\Users\User\Desktop\All About Python  
etecting_from_image.py
```

```
Found 10 birds!
```

```
Bird Location: 331 471 101 101
```

```
Center Position of the Bird: [381.5, 521.5]
```

```
Bird Location: 55 151 68 68
```

```
Center Position of the Bird: [89.0, 185.0]
```

```
Bird Location: 211 162 45 45
```

```
Center Position of the Bird: [233.5, 184.5]
```

```
Bird Location: 64 164 45 45
```

```
Center Position of the Bird: [86.5, 186.5]
```

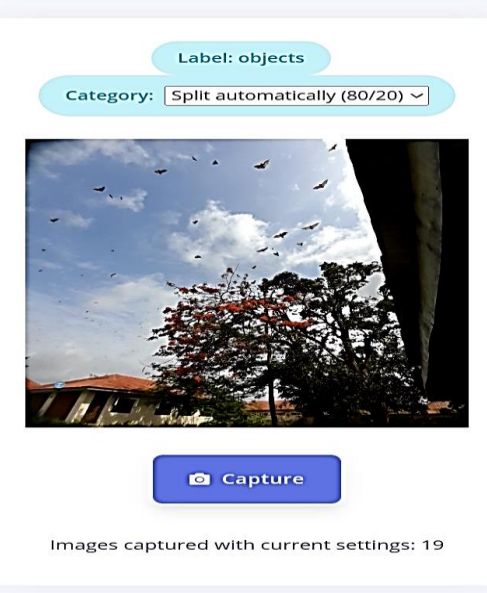
```
Bird Location: 580 220 45 45
```

Future Work (More Data Collection)

10:28 34%
one.edgeimpulse.com

Data collection

Label: objects
Category: Split automatically (80/20)



Capture

Images captured with current settings: 19



EDGE IMPULSE

- Dashboard
- Devices
- Data acquisition
- Impulse design
 - Create impulse
- EON Tuner
- Retrain model
- Live classification
- Model testing
- Versioning
- Deployment

DATA COLLECTED: -

TRAIN / TEST S...

Record new data [Connect using WebUSB](#)

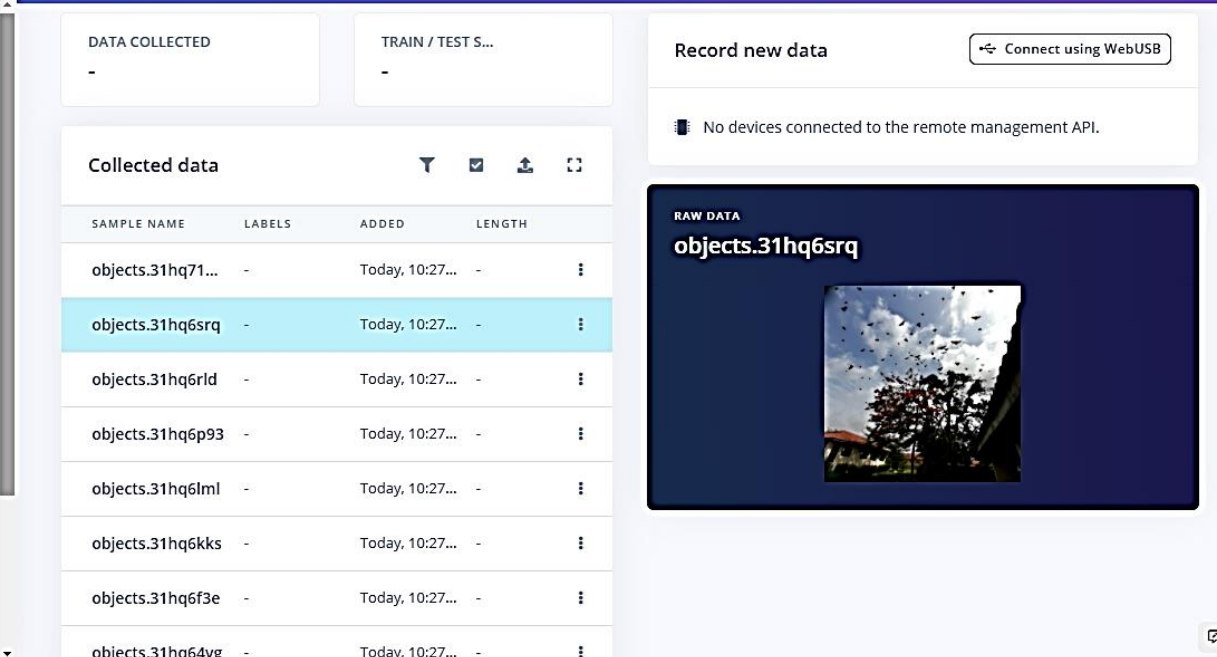
No devices connected to the remote management API.

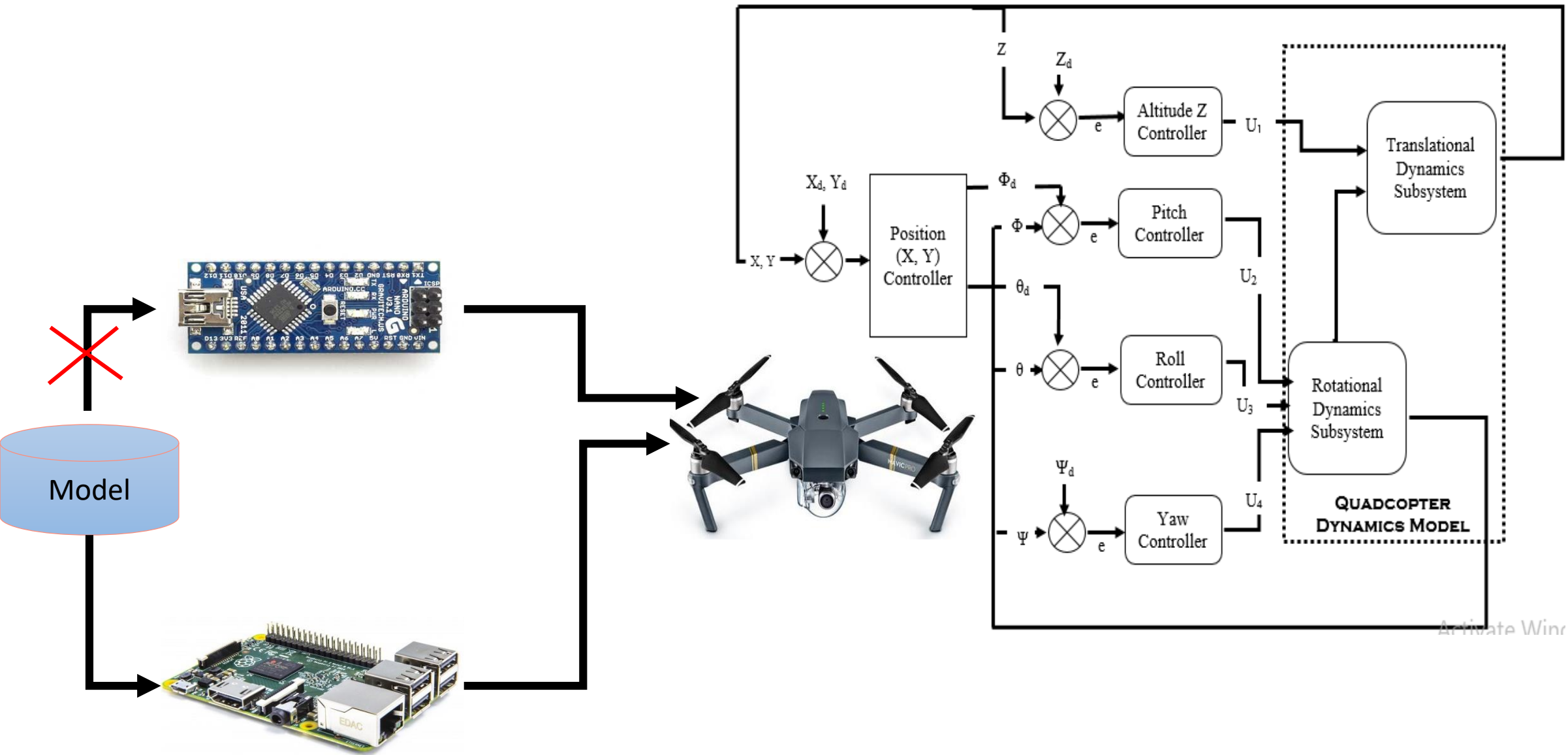
Collected data

| SAMPLE NAME | LABELS | ADDED | LENGTH |
|-------------------|--------|-----------------|--------|
| objects.31hq71... | - | Today, 10:27... | - |
| objects.31hq6srq | - | Today, 10:27... | - |
| objects.31hq6rld | - | Today, 10:27... | - |
| objects.31hq6p93 | - | Today, 10:27... | - |
| objects.31hq6lml | - | Today, 10:27... | - |
| objects.31hq6kks | - | Today, 10:27... | - |
| objects.31hq6f3e | - | Today, 10:27... | - |
| objects.31hq64vg | - | Today, 10:27... | - |

RAW DATA

objects.31hq6srq



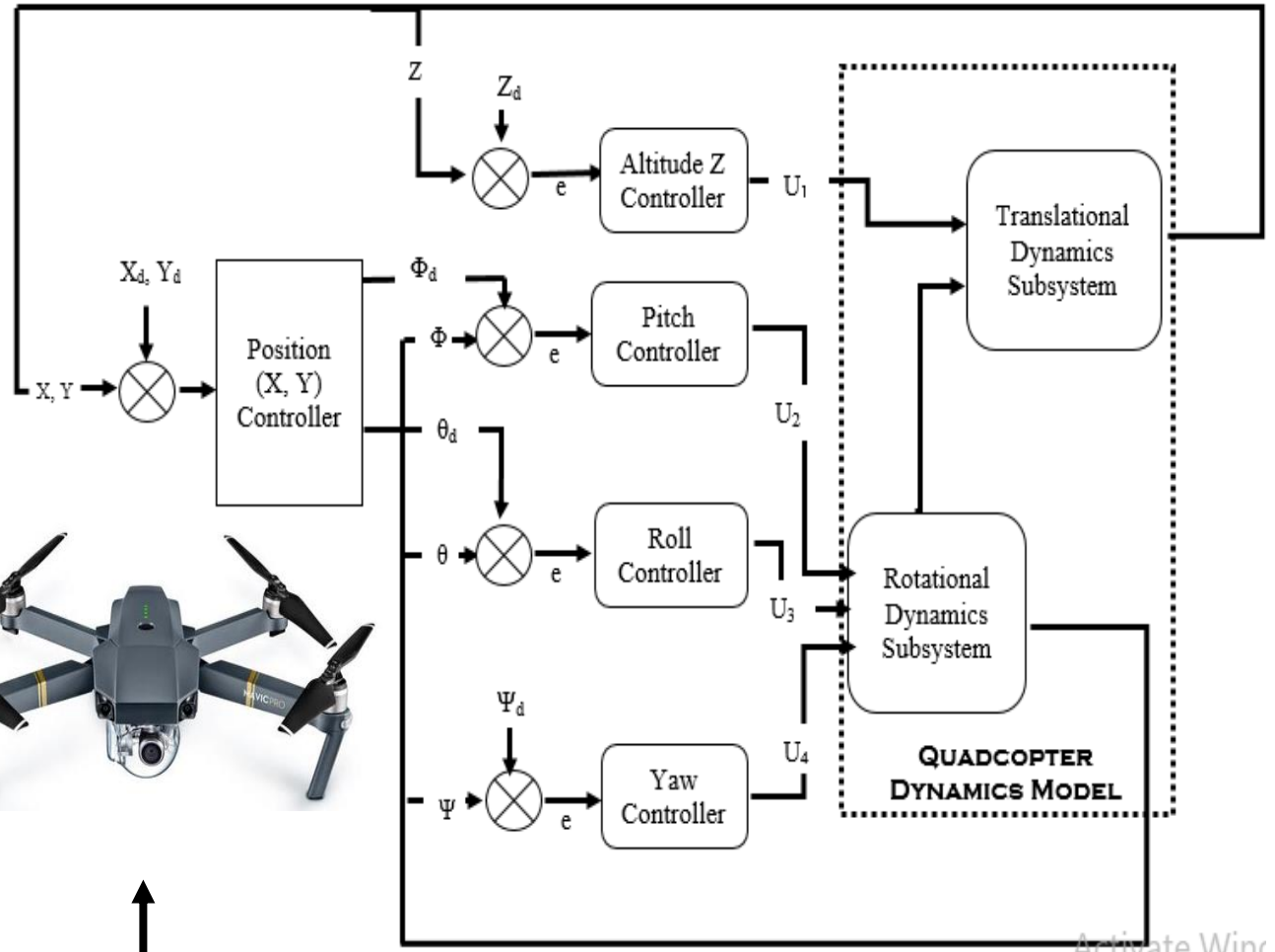
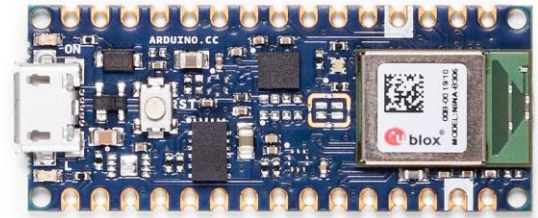


Power consumption
 Additional weight
 Complexity

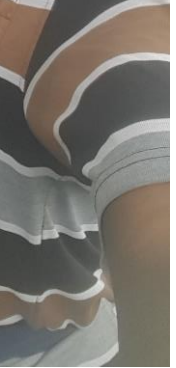
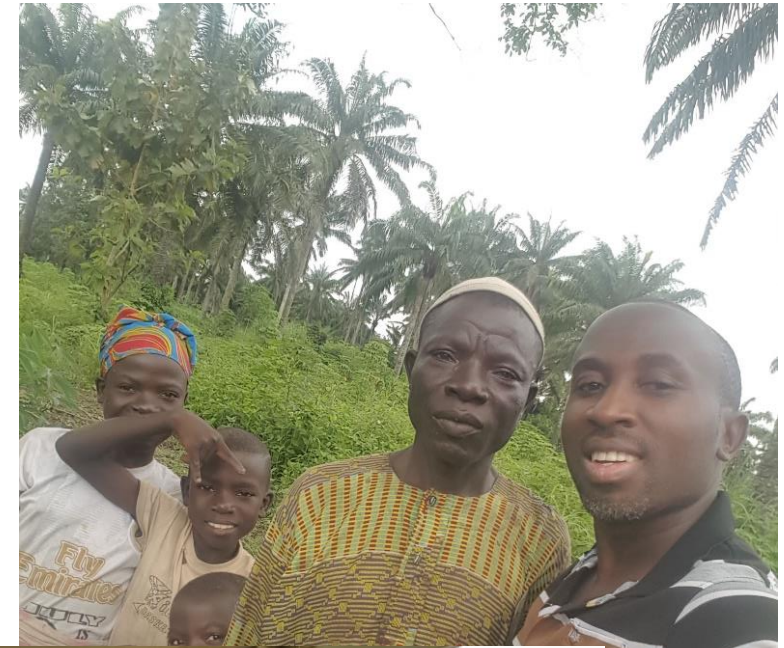
Future Work (Model Deployment)

Model

 **EDGE IMPULSE**



Artivate Winr



CONCLUSION

This work provides an automatic and faster approach to pest prevention and dispersal on farmland. With this, farmers don't need to be on site every time to scare birds off and beyond that, agricultural productivity will increase exponentially.

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THANK YOU...