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Monitoring of Migration of Harmful Sparrow Birds in a Rice Farm Using Convolutional Neural Network (CNN) Model

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Abstract
This paper presents the development of a trained convolutional neural network (CNN) model to monitor migration of harmful sparrow birds in a rice farm. 98% of grain eaters are sparrow birds and there is need to monitor their movements across rice farms so as to reduce losses. This study grouped rice birds into beneficial (insectivorous) birds that feed on rice insect pests and the harmful sparrow birds that feed on the rice grain. Here, the prevalent harmful sparrow birds were identified and the different images of the birds were captured by high resolution cameras to form part of the datasets for the training of the CNN model. To monitor the movement of different species of harmful sparrow birds in and out of a rice farm, a total of 85,000 images of sparrow birds (100 images of the sparrow birds captured from the selected rice farm and 84,900 images of different sparrow birds across the globe obtained from internet) were pre-processed to form datasets for the training of the CNN model in Google Colab platform using python programming. If the model identified a bird other than the sparrow birds, it recognized it as beneficial birds and allowed it to continue pest control in the farm. A bird repository database was developed along with the dataset which contained information about the different species of the sparrow birds. Then, an algorithm was developed to use the classification of the CNN model to match the bird repository database so as to get information about the specie and origin of any sparrow bird that entered the rice farm and sent such information to the farmer as short message service (SMS). It helped the farmer to know whether to apply more aggressive and consistent bird deterrence or early harvesting of the crop in the rice farm depending on the frequency and nature of the sparrow bird detected. This model had accuracy of 98% in the detection and classification of the sparrow birds and will be of importance to agricultural researchers studying bird migration across farms.

Keywords: Convolutional Neural Network, Migration, Harmful Sparrow Bird, Image Classification, Rice Farm

1. Introduction

Bird migration is the regular seasonal movement of birds, often north and south, between breeding wintering grounds (Kutschera & Niklas, 2014). According to Greenberg and Marra (2016); Mettke-Hofmann and Greenberg (2016); Mettke-Hofmann and Gwinner (2016) birds are in search of climates that will provide more food and daylight hours for them. Some birds migrate to take advantage of seasonal resources, especially food, so that they can breed successfully. Some migrations of birds are short, but many birds make truly epic journeys, crossing continents, deserts and oceans. Going by research works presented by Piersma et al (2018); Rappole (2015); Russell, Yom-Tov and Geffen (2018), it was discovered that some birds can move from Arctic to Antarctic regions and enjoy two summers in a year. Hence, this research work will develop a convolutional neural network (CNN) model that will be able to identify and classify sparrow birds' migration across rice farm. Machine learning has also applied image recognition to vineyard and agricultural objects with 80.6% accuracy (Paolo 2019). Oluwole, Adefemi and Ade-Omoway (2020), presented a bird identification system based on bird features identification-image processing has been deployed with Raspberry pi. The device utilized a model trained separately using Haar features,Histogram of Oriented Gradients (HOG) and Local Binary Patterns(LBP), Python and Open CV library software. The system achieved 76% highest accuracy from Harr, 72% from LBP and 27% from HOG, but did not specific in the particular bird to identify.CNN can learn highly abstracted features; especially spatial data and once trained can correctly identify the features of an input image. (CNN affords comparatively easier implementation because of the reduction of the number of trainable network parameters via the use of the weight sharing features and ability of the classification and feature extraction layers to learn together (Deepak 2017).

Intermediate terms calculation avoidance is consequently enabled in the CNN and the associated over-training of the network and its consequent poor predictions overcome. The inter-layers transfer functions weights are fine-tuned by feeding the errors backwards using back propagation algorithm. CNN needs a capable robust programming language. Python language suits CNN implementation because of its readability and dense syntax. Google Colab platform is also suitable as machine learning platform for image processing, recognition and classifications. The Raspberry pi 2 is a device (Small Computer) that was used for the Sparrow bird image preprocessing and video streaming (Ramesh, Srikanth and Srinath (2020). 98% of grain eaters are sparrow birds and there is need to monitor their movements across rice farms so as to reduce losses. This study grouped rice birds into beneficial (insectivorous) birds that feed on rice insect pests and the harmful sparrow birds that feed on the rice grain. Bird migration makes it difficult for a particular sparrow bird to be localized to a particular locality for a very long period of time and using only such local image to form the dataset in training a CNN model for image recognition of such specie will be ineffective.

Once the particular specie leaves the rice farm, the CNN model would assume that there were no sparrow birds present in the farm and classify other birds as beneficial insectivorous birds without detecting any harmful sparrow birds that entered from other locations outside the rice farm since the dataset was limited to the birds within the farm. This inability of the model to detect harmful sparrow birds from other locations would lead to excessive destruction of the rice farm by these unnoticed dangerous sparrow birds that immigrated into the rice farm. However, if 85,000 different images of the harmful sparrow birds were used as the training dataset for the model, it would be able to detect any harmful sparrow bird that entered the rice farm and send timely information to the farmer to tackle the menace. A lot of researchers have carried out studies to monitor situations in the farm ranging from bird detection, leave identification for diseases and general farm surveillance but none has focused on the identification of a specific harmful bird. No researcher has classified birds in the rice farm as beneficial and harmful. Most of the researchers considered birds as pest and nuisance that needed to be scared away. This work covered material and data collection, methodology, results and discussion and conclusion.

2.0 Material and methods

Materials are tools that were deployed to ensure that the objectives of this research work were achieved. The materials used in the work were grouped into two main headings: Hardware and Software Materials.

2.1 Hardware Materials

These are those physical tools that can be touched which are deployed in the course of this research work. Some basic ones are included:

(a) Cameras

These were the devices strategically positioned in the farm to capture the different images of the sparrow birds as shown in plate 2.1. They provided the much-needed image data sets for the training of the convolutional neural network. The camera used here was a lithium battery powered 4k digital camera that runs for 3 days when fully charged. It utilized idle mode in the night and that led to increased battery life of up to 5 days. The sparrow birds are diurnal birds and do not move in the night, hence the digital camera was programmed to enter idle mode when in darkness but became activated in the presence of light so as to extend the battery life. The camera has internal capacity of 1 giga byte and external memory card of 1 tera byte.

Plate 2.1: High resolution digital 4K camera

The image in plate 2.2 was captured by the digital 4k camera in plate 2.1. Similarly, the different sparrow birds' images in plate 2.3 were obtained from different internet sources and they were combined with the different images as captured in plate 2.2 by camera in plate 2.1. These combined sparrow birds' images were preprocessed by raspberry pi using python language to convert the images into the image format joint photographic group (JPG) and 3 dimensions (224, 224, 3) pixels to form the dataset for the training of the Convolutional neural network (CNN) using the Appendices I and II.

Plate 2.2: Image of sparrow bird captured in a rice farm

Plate: 2.3: Images of different harmful sparrow birds from other location (Source: Internet)

(b) Raspberry pi 5

The Raspberry pi 5 is a device (Small Computer) that was used for the Sparrow bird image preprocessing and video streaming. It operated on Raspbian operating system, a version of Linux and a modified version of Debian. The preferred language used was Python which was used to develop the control programme. The developed CNN model was also deployed in the raspberry pi 5 since it has graphic processing unit (GPU) on which the model can be deployed. The raspberry pi 5 used wireless fidelity (wifi) to connect to cameras in the farm and also used internet connectivity to send SMS to the farmer about bird migration in the rice farm (Ankush et al 2018; Oluwole, Adefemi & Ade-Omowaye 2020).

2.2 Software Materials

These are programmes and software deployed in the realization of the objectives of this research work. Some of the software materials were discussed as follow:

(a) Training Method

Here, the training method for this research was back- propagation (BP) training method. This method used the data sets to train the convolutional neural network. The learning process in an artificial neural network (ANN) entails adjusting the weights associated to the transfer functions between neurons comparing artificial neural network (ANN) output with observed data. The back-propagation (BP) was used to train the feed-forward neural network to minimize error (which is the difference between the desired output and the calculated output). However, a large network which used too many nodes would become over-trained, causing it to memorize the training data resulting in poor predictions and consumed a lot of money. This training was repeated until either the specified error rate was obtained or the number of training cycles (Epochs) was reached (Paolo 2019; Ramesh, Srikanth and Srinath 2020).

(b) Python Language

It is a widely used programming language because of its readability and dense syntax. It was used to train the model in Google Colab platform for rice bird recognition and classifications (Divyansh and Patro 2023; Ramesh and Srinath 2020).

2.3 Data Collection

Here, data collection was divided into two stages:

(a) The use of questionnaires to identify the different sparrow birds in the selected rice farms.
(b) The capturing of the different images of the selected Sparrow birds with Camera

(a) Data Collection using Questionnaires

In the course of this research, twenty rice farmers were interviewed and five rice farms were selected in Nenwe community of Aninri local government area in Enugu state, Nigeria, so as to identify the prevalent harmful sparrow birds in the selected farms in Nenwe. Questionnaires were distributed to the selected twenty rice farmers in Nenwe so as to extract vital information from them as shown in Appendix III. The questionnaires were marked with serial numbers Q1 to Q20 for easy tracking and collection of the distributed questionnaires and to protect the privacy of the farmers. Benefits of the questionnaires in this research study are as follows:

- It provided the information that sparrow birds are the most dangerous birds affecting rice production negatively in Nenwe community.
- It provided information that all the birds in the rice are not harmful.
- It provided the information that some birds in the farm feed on insect pests that attack the rice plant there by performing biological pest control in the farm.
- It provided the information that squirrel is the predator for the harmful sparrow birds.
- It also provided an avenue that helped in obtaining information from different rice farmers during the course of this research.
- It was with this questionnaire that permission was granted to use the selected rice farms in plates 2.4 and 2.5 for this research study.

(b) Image Capturing of the Sparrow Birds

100 different images of the harmful sparrow birds as shown in plates 2.2 and 2.3 were captured using high resolution 4k digital camera as shown in plate 2.1. Also rice farms in plates 2.4 and 2.5 were captured with some sparrow birds in them by the camera in plate 2.1 in an attempt to capture harmful sparrow birds in the selected rice farm. Plate 2.5 showed one of the selected rice farms with images of some sparrow birds. In the course of this study, the number of cameras deployed, angles of camera deployment and range (separation distance) of the cameras were determined using equations 2.1 and 2.2. Also, Table 2.1 showed the number of cameras, angles of deployment, separating distances of the cameras for a given area and perimeter of a rice farm.

$$No\ of\ Cameras = \frac{360}{Relative\ Angle\ of\ Deployment} \tag{2.1}$$

$$Separation\ Distance\ of\ Camera = \frac{Perimeter\ of\ Rice\ Farm}{No\ of\ Cameras} \tag{2.2}$$

The cameras were deployed in such a way as to cover the 360 degree overview of the rice farm and take images every 10 seconds and sends to the raspberry pi 5 for pre-processing and further classification of the image by the CNN model housed in the raspberry pi 5.

Table 2.1: Deployments of cameras based on the size of the five selected rice farms

Area of Rice Farm (Square Meter)	**Perimeter Of Rice Farm (Meters)**	**Relative angle of deployment**	**Separation Distance of the Cameras (Meters)**	**Number of Cameras**
1500	160	90 Degrees	40	4
From 1500 to 3000	From 160 to 220	60 Degrees	37	6
From 3000 to 6000	From 220 to 320	45 Degrees	40	8
From 6000 to 12000 (1 hectare)	From 320 to 440	30 Degrees	37	12
From 12000 to 24000 (2 hectares)	From 440 to 640	22.5 Degrees	40	16

Plate 2.4: Rice Farm at Umunkpochi, Emudo, Nenwe in Aninri of Enugu State, Nigeria.

Plate 2.5: Rice Farm at Umunkwoga, Emudo, Nenwe in Aninri of Enugu state showing sparrow birds.

2.4 Methodology

2.4.1 Image Pre-processing for Development of Dataset for Model Training

Here, the dataset for model training was generated from the flow chart in Figure 3.1.

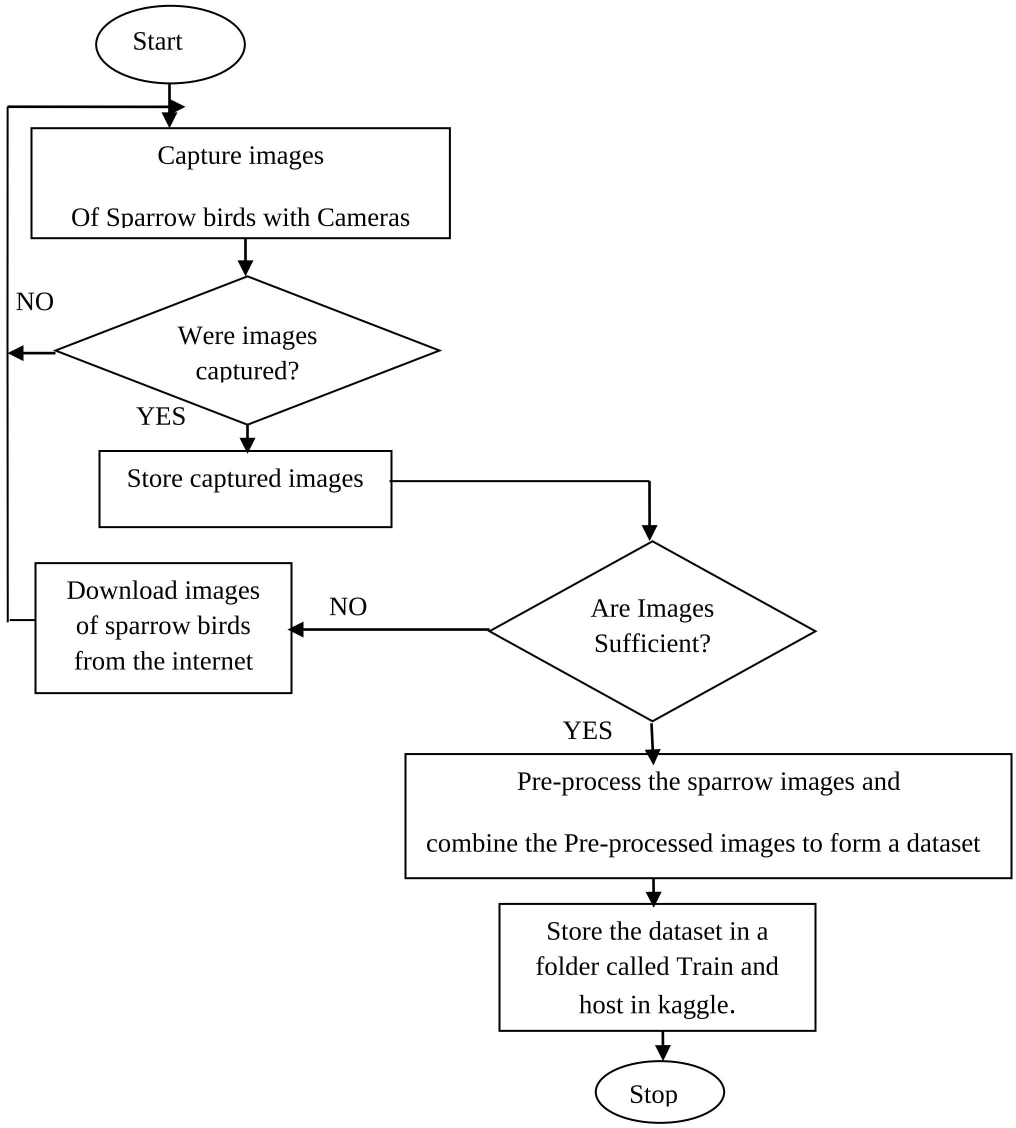


Figure 2.1: Flowchart for building of training dataset for CNN model training

2.4.2 Model Development and Training

In the development of this convolutional neural network (CNN), a pre-trained high efficient model called efficientnetb5 was frozen of its weight and used in a process of transfer intelligence as a foundation for the new CNN model. The output of the pre-trained model was removed and the convolutional base for the new model was introduced so as to capture the image format for the developed model and the dense layer was added so as to obtain an output for the developed model (Probavathi and Kanmani 2021). The model development flow chart was shown in figure 2.2.

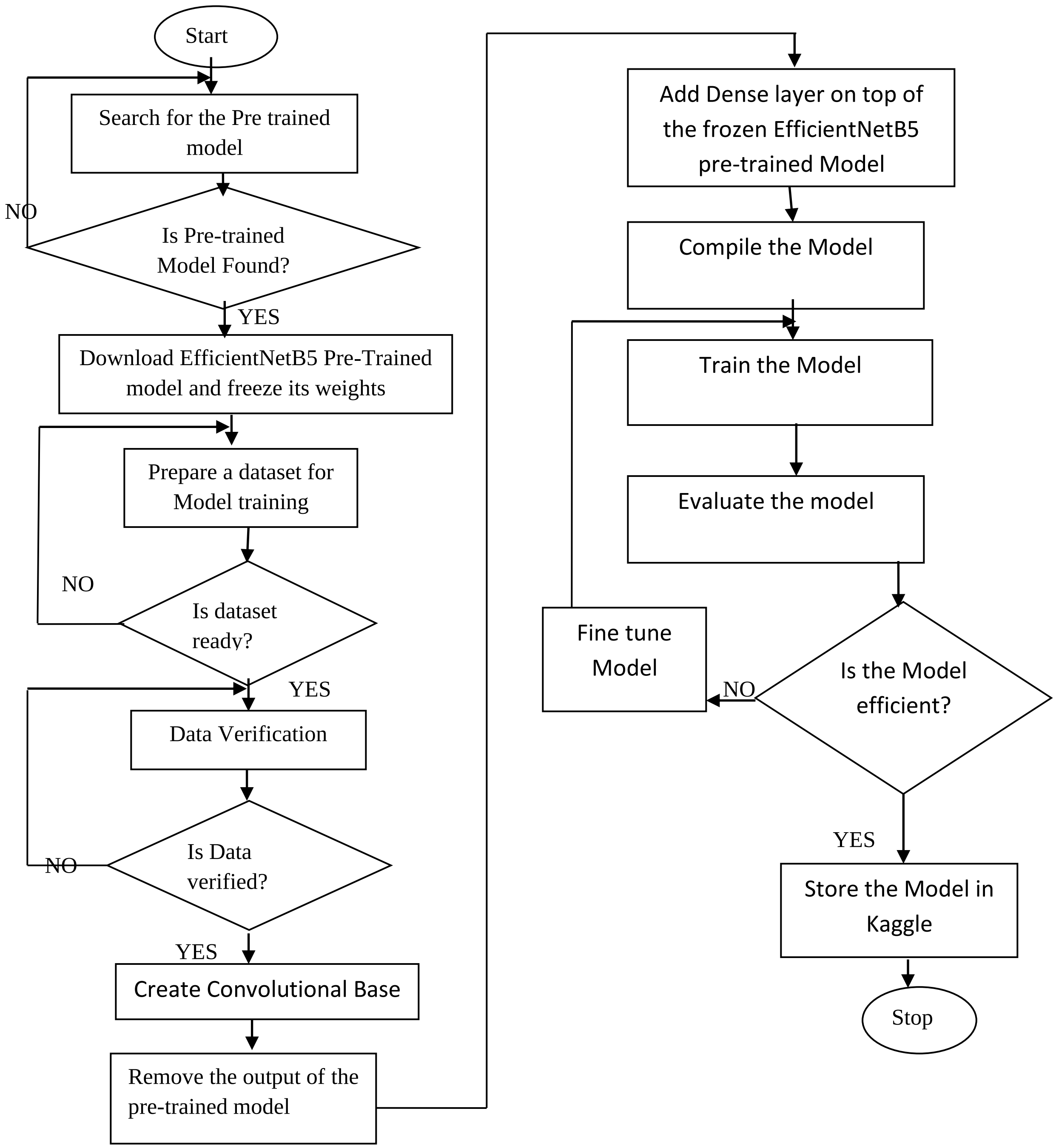


Figure 2.2: Flowchart for building of CNN model for monitoring of harmful sparrow birds in a rice farm

The flowchart in Figure 2.2 was followed to produce the CNN model in Figure 2.3 which showed the sequence of the convolutional neural network (CNN) model developed in the course of this research with increased number of trainable parameters due to augmentation, dropout and unfreezing of the weights of the pre-trained efficientnetb5 model used as the foundation of the building of this model.

Layer (type)	Output Shape	Param #
inputLayer (InputLayer)	[(None, 224, 224, 3)]	0
AugmentationLayer (Sequential)	(None, None, None, None)	0
efficientnetb5 (Functional)	(None, 2048)	28513527
dense_3 (Dense)	(None, 1024)	2098176
activation_2 (Activation)	(None, 1024)	0
batch_normalization_2 (BatchNormalization)	(None, 1024)	4096
dropout_2 (Dropout)	(None, 1024)	0
dense_4 (Dense)	(None, 512)	524800
activation_3 (Activation)	(None, 512)	0
batch_normalization_3 (BatchNormalization)	(None, 512)	2048
dropout_3 (Dropout)	(None, 512)	0
dense_5 (Dense)	(None, 525)	269325
activationLayer (Activation)	(None, 525)	0

Total params: 31411972 (119.83 MB)
Trainable params: 31063421 (118.50 MB)
Non-trainable params: 348551 (1.33 MB)

Figure 2.3: CNN model for sparrow birds' identification and characterization to monitor sparrow birds' migration in a rice farm showing inputs and output layers with more trainable parameters

2.4.3 Model Training

The developed CNN model in Figure 2.3 was trained using back-propagation method in google colab platform with 85,000 images of sparrow birds (combined 100 images from the farm and 84900 images from other sources) as preprocessed by the flowchart in Figure 2.1 and python programme in Appendix I (Deepak et al 2017).

2.4.4 Development of Flow Chart to Monitor Sparrow Bird Migration across the Rice Farm

Figure 2.4 showed the flow chart for the development of this convolutional neural network based sparrow birds monitoring across rice farms.

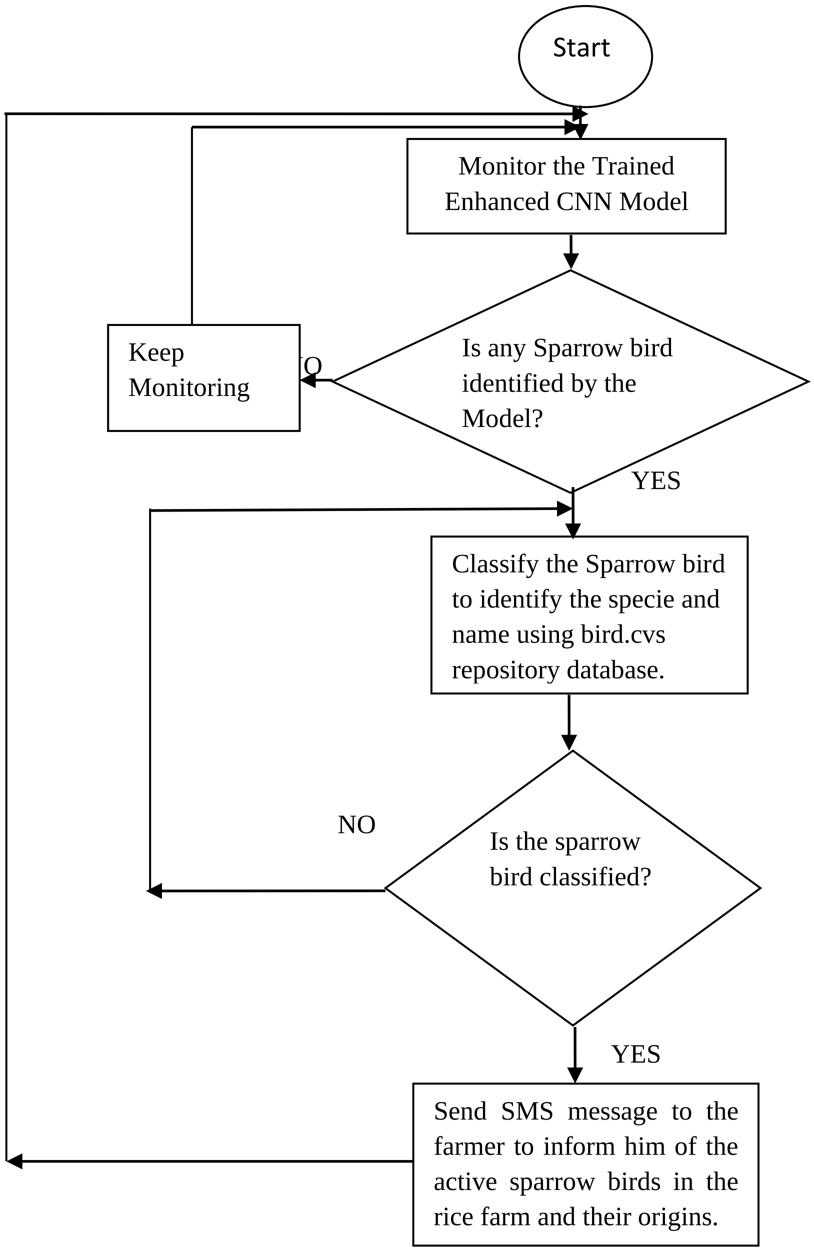


Figure 2.4: Flowchart to monitor sparrow birds' migration across the rice farm

3.0 Results and Discussions

3.1 Results of Information obtained from the questionnaires

The questionnaires returned by the farmers as shown in Table 3.1 were used to extract information that sparrow bird was the most dangerous bird in the selected rice farms, the information about beneficial (insectivorous) birds, squirrel as the potential predator of the harmful sparrow birds as shown in Tables 3.2, 3.3 and 3.4 respectively. The Table 3.1 showed the total number of questionnaires distributed to the farmers, total number returned and the total number not returned. From Table 3.1,

the compliance percentage of the selected farmers was calculated with equation (3.1).

$$C = \frac{[(QR) \times 100]}{(QNR+QR)} \tag{3.1}$$

$where\ C = Compliance\ Percentage\ of\ Selected\ Farmers$

QR = Number of Questionnaires Returned

QNR = Number of Questionnaires not Returned.

Table 3.1: Number of questionnaires distributed and the number of questionnaires returned.

Distributed Questionnaires	Returned Questionnaires	Not Returned Questionnaires
Q1	-----	Q1
Q2	Q2	---
Q3	Q3	---
Q4	Q4	---
Q5	Q5	---
Q6	Q6	---
Q7	Q7	----
Q8	Q8	---
Q9	Q9	----
Q10	Q10	----
Q11	Q11	---
Q12	Q12	---
Q13	Q13	---
Q14	Q14	---
Q15	Q15	---
Q16	Q16	---
Q17	Q17	---
Q18	Q18	---
Q19	Q19	---
Q20	Q20	---

Also, Table 3.2 showed that the information about the harmful bird in the rice farms in Nenwe was equally obtained from the questionnaire. Table 3.2 was used to determine the percentage of the selected farmers that agreed that sparrow bird was the harmful bird for rice production in Nenwe community as calculated using equation (3.2).

$$F = \frac{NFA \times 100}{NFW} \tag{3.2}$$

F = Percentage of the selected farmers that agreed that sparrow birds were the harmful rice birds.

NFA =Number of the selected farmers that agreed that sparrow birds were the rice harmful birds.

NFW = Number of the selected farmers that returned the questionnaires.

Table 3.3 provided information about beneficial birds and their biological pest control.

Table 3.2: Information about the harmful rice bird (sparrow)

Distributed Questionnaires	Returned Questionnaires	Most Harmful Rice Bird
Q1	-----	---
Q2	Q2	Ashi (Sparrow Bird)
Q3	Q3	Ashi (Sparrow Bird)
Q4	Q4	Ashi (Sparrow Bird)
Q5	Q5	Ashi (Sparrow Bird)
Q6	Q6	Ashi (Sparrow Bird)
Q7	Q7	Ashi (Sparrow Bird)
Q8	Q8	Ashi (Sparrow Bird)
Q9	Q9	Ashi (Sparrow Bird)
Q10	Q10	Ashi (Sparrow Bird)
Q11	Q11	Ashi (Sparrow Bird)
Q12	Q12	Ashi (Sparrow Bird)
Q13	Q13	Ashi (Sparrow Bird)
Q14	Q14	Ashi (Sparrow Bird)
Q15	Q15	Ashi (Sparrow Bird)
Q16	Q16	No Information
Q17	Q17	Ashi (Sparrow Bird)
Q18	Q18	Ashi (Sparrow Bird)
Q19	Q19	Ashi (Sparrow Bird)
Q20	Q20	No Information

Table 3.3: Information about the beneficial rice birds

Distributed Questionnaires	Returned Questionnaires	Are there Some Birds that feed on Insects in the Rice Farm (Beneficial Birds)
Q1	-----	---
Q2	Q2	Yes
Q3	Q3	Yes
Q4	Q4	Yes
Q5	Q5	Yes
Q6	Q6	Yes
Q7	Q7	Yes
Q8	Q8	Yes
Q9	Q9	No Information
Q10	Q10	Yes
Q11	Q11	Yes
Q12	Q12	Yes
Q13	Q13	Yes
Q14	Q14	Yes
Q15	Q15	Yes
Q16	Q16	Yes
Q17	Q17	Yes
Q18	Q18	Yes
Q19	Q19	Yes
Q20	Q20	Yes

Table 3.3 used the collected questionnaires to show the opinions of the selected farmers about the beneficial birds in the rice farm and the percentage of the selected farmers that agreed on the presence of beneficial birds in a rice farm was calculated using equation (3.3). Similarly, Table 3.4 was used to extract the information that squirrel was the potential predator of the sparrow birds.

$F = \frac{FA \times 100}{TF}$ (3.3)

F = Percentage of Farmers that agree that some birds are beneficial

TF = Total Number of Returned Questionnaires

Table 3.4: Information about the predator (Squirrel)

Distributed Questionnaires	Returned Questionnaires	Name of the Predator of the harmful Sparrow bird
Q1	-----	---
Q2	Q2	Squirrel (Uriri)
Q3	Q3	Squirrel (Uriri)
Q4	Q4	Squirrel (Uriri)
Q5	Q5	Squirrel (Uriri)
Q6	Q6	Squirrel (Uriri)
Q7	Q7	Squirrel (Uriri)
Q8	Q8	Squirrel (Uriri)
Q9	Q9	No Information
Q10	Q10	Squirrel (Uriri)
Q11	Q11	Squirrel (Uriri)
Q12	Q12	Squirrel (Uriri)
Q13	Q13	Squirrel (Uriri)
Q14	Q14	Squirrel (Uriri)
Q15	Q15	Squirrel (Uriri)
Q16	Q16	Squirrel (Uriri)
Q17	Q17	Squirrel (Uriri)
Q18	Q18	Squirrel (Uriri)
Q19	Q19	Squirrel (Uriri)
Q20	Q20	Squirrel (Uriri)

Table 3.4 used the collected questionnaires to show the opinions of the selected farmers about the predator for the harmful sparrow bird in the rice farm and the percentage of the selected farmers that agreed was calculated using equation (3.4). $F = \frac{FP \times 100}{TF}$ (4.4)

Where, F = Percentage of Farmers that agreed that squirrel was the predator for the harmful sparrow birds

FP = Number of farmers that agreed that the predator of sparrows was squirrel.

TF = Number of farmers that filled and returned their questionnaires.

3.2 Results of Training and Validation Accuracies and Losses

In Figure 2.3, the developed enhanced CNN model for bird classification in a rice farm was trained with a dataset of 84,900 different images of sparrow birds across the globe and 100 different images of the captured sparrow birds in the rice farm and the training results were obtained and shown in Table 3.5 and Figures 3.1 and 3.2.

```
Epoch 1/20
2419/2419 [==============================] - 1135s 439ms/step - loss: 5.7628 - accuracy: 0.0573 - val_loss: 4.0439 - val_accuracy: 0.2731 - lr: 1.0000e-05
Epoch 2/20
2419/2419 [==============================] - 1059s 438ms/step - loss: 4.0508 - accuracy: 0.2440 - val_loss: 2.6073 - val_accuracy: 0.5829 - lr: 1.0000e-05
Epoch 3/20
2419/2419 [==============================] - 1056s 437ms/step - loss: 2.8842 - accuracy: 0.4573 - val_loss: 1.5923 - val_accuracy: 0.7657 - lr: 1.0000e-05
Epoch 4/20
2419/2419 [==============================] - 1055s 436ms/step - loss: 2.0255 - accuracy: 0.6284 - val_loss: 0.9710 - val_accuracy: 0.8484 - lr: 1.0000e-05
Epoch 5/20
2419/2419 [==============================] - 1055s 436ms/step - loss: 1.4528 - accuracy: 0.7362 - val_loss: 0.6386 - val_accuracy: 0.8899 - lr: 1.0000e-05
Epoch 6/20
2419/2419 [==============================] - 1055s 436ms/step - loss: 1.0776 - accuracy: 0.8004 - val_loss: 0.4567 - val_accuracy: 0.9139 - lr: 1.0000e-05
Epoch 7/20
2419/2419 [==============================] - 1052s 435ms/step - loss: 0.8295 - accuracy: 0.8440 - val_loss: 0.3471 - val_accuracy: 0.9242 - lr: 1.0000e-05
Epoch 8/20
2419/2419 [==============================] - 1052s 435ms/step - loss: 0.6563 - accuracy: 0.8733 - val_loss: 0.2818 - val_accuracy: 0.9387 - lr: 1.0000e-05
Epoch 9/20
2419/2419 [==============================] - 1051s 435ms/step - loss: 0.5369 - accuracy: 0.8946 - val_loss: 0.2401 - val_accuracy: 0.9459 - lr: 1.0000e-05
Epoch 10/20
2419/2419 [==============================] - 1053s 435ms/step - loss: 0.4492 - accuracy: 0.9087 - val_loss: 0.1992 - val_accuracy: 0.9531 - lr: 1.0000e-05
Epoch 11/20
2419/2419 [==============================] - 1053s 435ms/step - loss: 0.3802 - accuracy: 0.9227 - val_loss: 0.1895 - val_accuracy: 0.9562 - lr: 1.0000e-05
Epoch 12/20
2419/2419 [==============================] - 1054s 436ms/step - loss: 0.3254 - accuracy: 0.9331 - val_loss: 0.1751 - val_accuracy: 0.9554 - lr: 1.0000e-05
Epoch 13/20
2419/2419 [==============================] - 1052s 435ms/step - loss: 0.2811 - accuracy: 0.9412 - val_loss: 0.1577 - val_accuracy: 0.9608 - lr: 1.0000e-05
Epoch 14/20
2419/2419 [==============================] - 1050s 434ms/step - loss: 0.2468 - accuracy: 0.9486 - val_loss: 0.1558 - val_accuracy: 0.9604 - lr: 1.0000e-05
Epoch 15/20
2419/2419 [==============================] - 1050s 434ms/step - loss: 0.2149 - accuracy: 0.9547 - val_loss: 0.1440 - val_accuracy: 0.9642 - lr: 1.0000e-05
Epoch 16/20
2419/2419 [==============================] - 1050s 434ms/step - loss: 0.1895 - accuracy: 0.9599 - val_loss: 0.1413 - val_accuracy: 0.9646 - lr: 1.0000e-05
Epoch 17/20
2419/2419 [==============================] - 1055s 436ms/step - loss: 0.1687 - accuracy: 0.9648 - val_loss: 0.1353 - val_accuracy: 0.9669 - lr: 1.0000e-05
Epoch 18/20
2419/2419 [==============================] - 1054s 436ms/step - loss: 0.1499 - accuracy: 0.9683 - val_loss: 0.1307 - val_accuracy: 0.9653 - lr: 1.0000e-05
Epoch 19/20
2419/2419 [==============================] - 1051s 434ms/step - loss: 0.1327 - accuracy: 0.9708 - val_loss: 0.1378 - val_accuracy: 0.9638 - lr: 1.0000e-05
Epoch 20/20
2419/2419 [==============================] - 1052s 435ms/step - loss: 0.1177 - accuracy: 0.9749 - val_loss: 0.1257 - val_accuracy: 0.9669 - lr: 1.0000e-05
```

Figure 3.1: Results of training of developed CNN model to monitor sparrow birds' migration in a rice farm with epoch=20 using 85,000 images of sparrow birds as the dataset

Table 3.5: Training and validation accuracies and losses for the CNN model with epoch=20

Epoch Number	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1/20	0.0573	5.7628	0.2731	4.0439
2/20	0.2440	4.0508	0.5829	2.6073
3/20	0.4573	2.8842	0.7657	1.5923
4/20	0.6284	2.0255	0.8484	0.9710
5/20	0.7362	1.4528	0.8899	0.6386
6/20	0.8004	1.0776	0.9139	0.4567
7/20	0.8448	0.8295	0.9242	0.3471
8/20	0.8733	0.6563	0.9387	0.2818
9/20	0.8946	0.5369	0.9459	0.2401
10/20	0.9087	0.4492	0.9531	0.1992
11/20	0.9227	0.3802	0.9562	0.1895
12/20	0.9331	0.3254	0.9554	0.1751
13/20	0.9412	0.2811	0.9688	0.1577
14/20	0.9486	0.2468	0.9684	0.1558
15/20	0.9547	0.2149	0.9642	0.1440
16/20	0.9599	0.1895	0.9646	0.1413
17/20	0.9648	0.1687	0.9669	0.1353
18/20	0.9683	0.1499	0.9653	0.1307
19/20	0.9708	0.1327	0.9638	0.1378
20/20	0.9749	0.1177	0.9669	0.1257

From the results in table 3.5, the developed CNN model to monitor migration of sparrow birds in a rice farm has increased number of trainable parameters as shown in figure 2.3 which after the training with dataset of 85,000 images of sparrow birds yielded very low training losses as shown in figures 3.1 and 3.2. Also, the validation loss was small with high validation and training accuracy of 97% as also shown in figures 3.1 and 3.2. This training was carried out in Google Colab platform with epoch of 20 and 85,000 preprocessed images of sparrow birds so as to obtain improved training and validation accuracies at highly reduced losses.

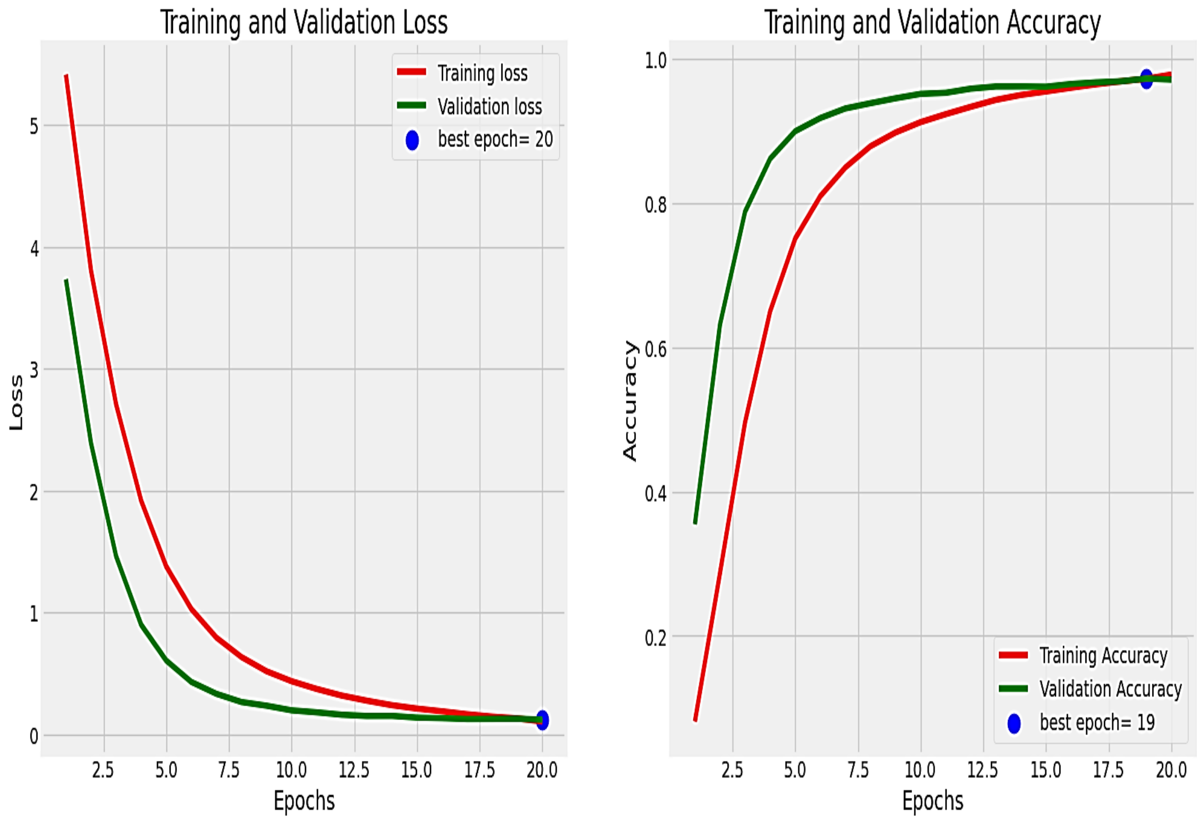


Figure 3.2: Training and validation accuracies and losses of the developed CNN model for monitoring of sparrow birds.

3.3 Results of Sparrow Bird Classification in Google Colab Platform

Figures 3.3 and 3.4 showed the results of the developed CNN model that classified sparrow bird images fed into it based on their species and name. The image of the bird in Figure 3.3 was one of the captured images from the rice farms used in this research and the path name of the bird was copied and pasted into the prediction path name of google colab. The developed CNN model hosted in kaggle was first downloaded from kaggle to google colab and then unzipped and moved to the google colab prediction environment for bird classification. Once the model classified the bird as sparrow, the developed algorithm used the classification by the model to interface with the bird repository database Bird.cvs to determine the type, specie and origin of the sparrow bird and send such information to the rice farmer so as to enable him know the migration of sparrow birds across his rice farm in other to know the right deterrent measure to apply and whether to engage on early harvesting to avoid heavy losses depending on the type of sparrow that was captured in the rice farm.

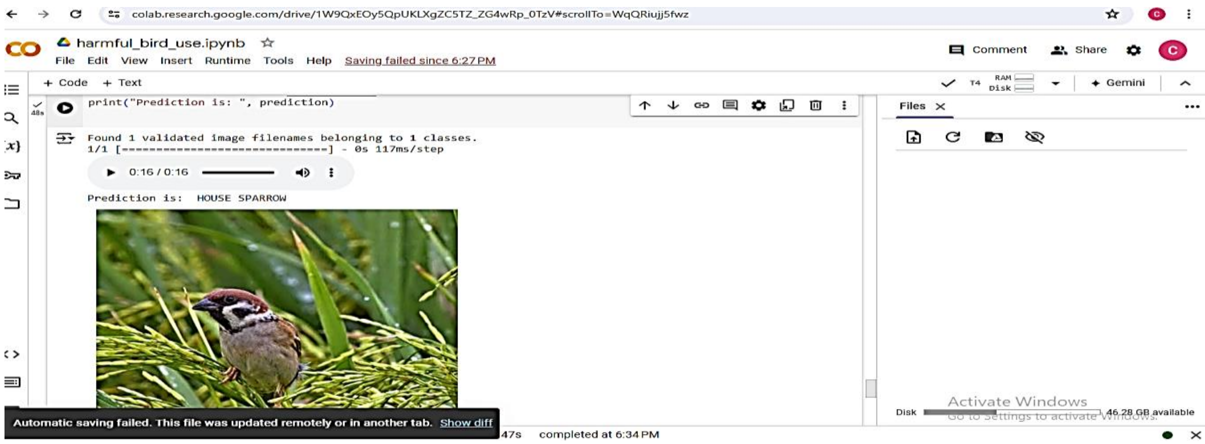


Figure 3.3: Result of Harmful bird Classification in Google Colab Platform using the sparrow bird in the selected rice farm

This Convolutional neural network (CNN) model was used to monitor the migration of sparrow birds across a rice farrm. The developed model was able to identify the presence of the different species of sparrow birds while the developed algorithm used the model's classification to interface with the bird repository database called birds.cvs so as to know the specie of the sparrow bird classified and the sparrow birds' origin, name and type and send such information to the farmer. Also in a google colab platform, the developed model was able to classify sparrow birds captured in the farm as shown in Figure 3.3 and also identify the sparrow birds from other locations as shown in Figure 3.4. This equally informed the rice farmers when heavy eating and more dangerous sparrow birds enter his rice farm and it will enable him to take quick decision on whether to employ fast and early harvesting so as to avoid heavy losses and even help the farmers to make the optimal decision on the best bird deterrence to employ in the rice farm. Also, Figure 3.5 showed the result of predictions of 700 different images of sparrow birds by the CNN model for monitoring of sparrow birds migration and the accuracy, precision, recall and f1 score of the model. Additionally, Figure 3.6 showed the bird.cvs repository database that the developed algorithm of Figure 2.4 used to get information about the identified sparrow birds that entered the farm and sent such information to the farmer through short message services (sms).

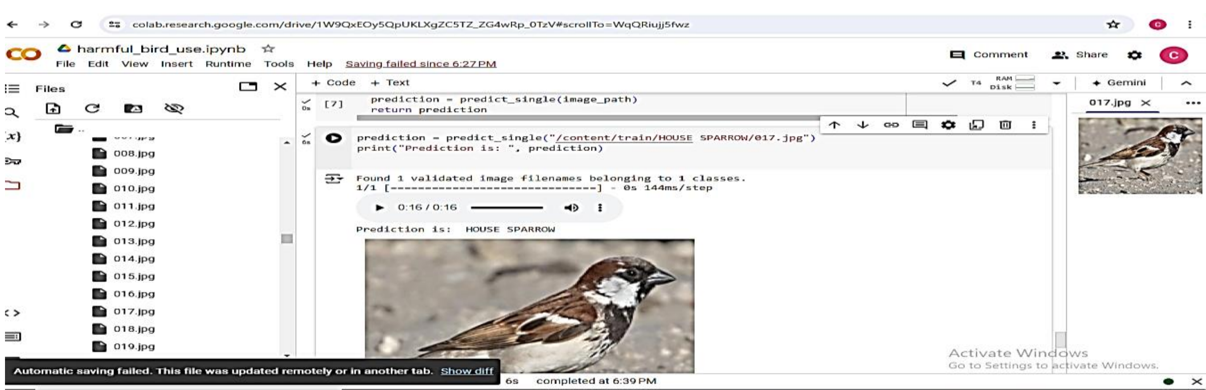
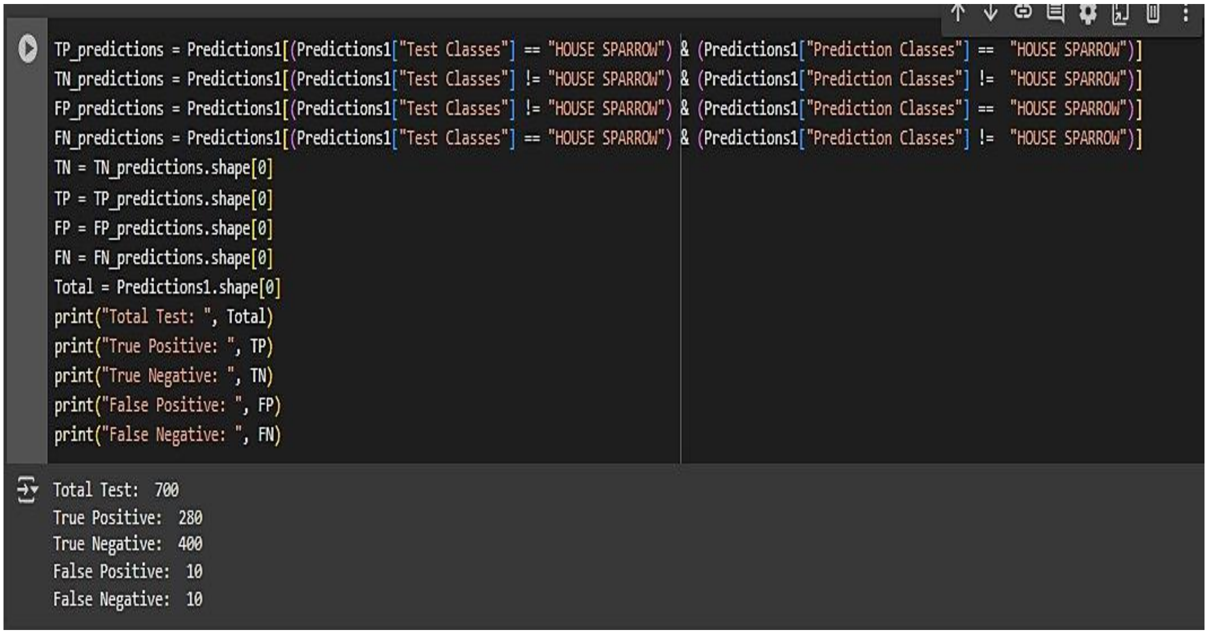


Figure 3.4: Result of Harmful bird Classification in Google Colab Platform using the sparrow birds from other locations.

From the result of total predictions of 700 images of sparrow birds as shown in Figure 3.5, showing the true positives, true negatives, false positives and false negatives, the model parameters were determined as shown:

- Accuracy = 97.2%
- Precision = 96.5%
- Recall = 0.965
- F1 Score = 0.965



```
TP_predictions = Predictions1[(Predictions1["Test Classes"] == "HOUSE SPARROW") & (Predictions1["Prediction Classes"] ==  "HOUSE SPARROW")]
TN_predictions = Predictions1[(Predictions1["Test Classes"] != "HOUSE SPARROW") & (Predictions1["Prediction Classes"] !=  "HOUSE SPARROW")]
FP_predictions = Predictions1[(Predictions1["Test Classes"] != "HOUSE SPARROW") & (Predictions1["Prediction Classes"] ==  "HOUSE SPARROW")]
FN_predictions = Predictions1[(Predictions1["Test Classes"] == "HOUSE SPARROW") & (Predictions1["Prediction Classes"] !=  "HOUSE SPARROW")]
TN = TN_predictions.shape[0]
TP = TP_predictions.shape[0]
FP = FP_predictions.shape[0]
FN = FN_predictions.shape[0]
Total = Predictions1.shape[0]
print("Total Test: ", Total)
print("True Positive: ", TP)
print("True Negative: ", TN)
print("False Positive: ", FP)
print("False Negative: ", FN)

Total Test:  700
True Positive:  280
True Negative:  400
False Positive:  10
False Negative:  10
```

Figure 3.5: Result of Model Testing

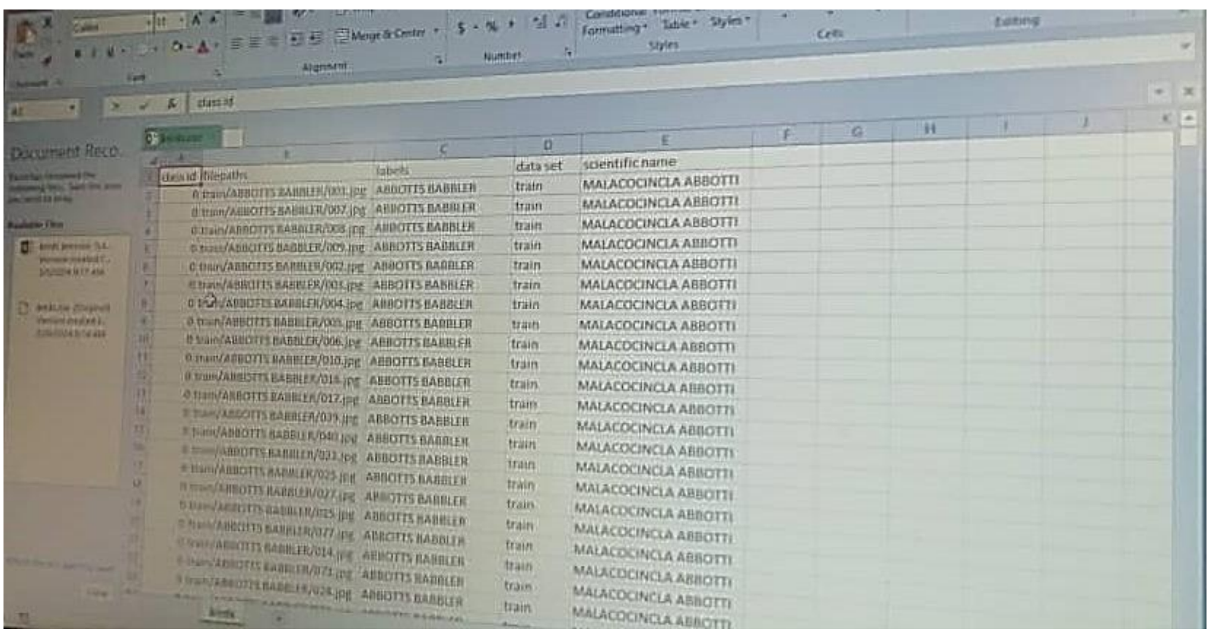


Figure 3.6: Bird repository database

4.0 Conclusion

This Convolutional neural network (CNN) model was used to monitor the migration of sparrow birds across a rice farm. The developed model was able to identify the presence of the sparrow bird while the developed algorithm used the model’s classification to interface with the bird repository database called birds.cvs so as to know the specie of the sparrow bird classified and the sparrow birds’ origin and sent such information to the farmer. Also in a google colab platform as shown in Figures 3.3 and 4.4, the developed model was able to classify sparrow birds captured in the farm and those from other sources. This equally informed the rice farmers when heavy eating and more dangerous sparrow birds entered their rice farms and it enabled them to take quick decision on whether to employ fast and early harvesting so as to avoid heavy losses. When the model was used for predictions as shown in Figure

3.5, it was able to give high accuracy (97.2%), Precision (96.5%), Recall (0.965) and F1score (0.965). With accuracy of 97% shown by the developed model as shown in section 3.3, it meant that for every 100 images of different sparrow birds captured and sent to it, it was able to characterize and identify 97 of such sparrow birds' images. This was better than the 76% accuracy presented by Oluwole, Adefemi, and Ade-Omowaye (2020), on a bird identification system based on bird features identification-image processing with Raspberry pi.

5.0 Recommendation

(i) The trained enhanced CNN model can be hosted in an internet enabled server and the raspberry pi in the farm would rely on it for image classification and recognition so as to enable it use the developed algorithm to either activate the speakers to generate predator sound or leave the beneficial birds to continue biological pest control in the farm. This can be possible if there is network coverage within the farm.
(ii) The trained CNN model with about 85,000 sparrow bird images across the globe can be used by Agriculture engineering researchers to study sparrow bird migration in a given locality.
(iii) There is need to capture more images of the sparrow birds by the cameras to be used as datasets for efficient training of the model.
(iv) Other pre-trained Convolutional neural network (CNN) like Res Net50, Regional Based Convolutional Neural Network (RCNN), or Single Shot multiBox Detector (SSD) can be modified and fine tuned for the same image classification and recognition and results compared to the EfficientNetB5.

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Appendix I

Program for Pre-processing of Captured and downloaded images of Sparrow Birds by Raspberry pi

```
pip install kaggle!
import warning
from sklearn.exceptions import ConvergenceWarning
warnings.filterwarnings("ignore", category=ConvergenceWarning)
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=UserWarning)
import itertools
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from PIL import Image
from sklearn.metrics import classification_report, f1_score , confusion_matrix
```

```
! pip install pillow

from PIL import Image
def resize_image(input_image_path, output_image_path, size):

    original_image = Image.open(input_image_path)
    resized_image = original_image.resize(size)
    resized_image.save(output_image_path)

# Example usage:
input_image_path = 'input_image.jpg'
output_image_path = 'output_image.jpg'
size = (224, 224)  # New size of the image (width, height)

resize_image(input_image_path, output_image_path, size)
```

Appendix II

Algorithm for the Pre-Processing of the Captured and Downloaded Images of the Sparrow Birds to Develop the Training Dataset

Step 1: Start

Step 2: Capture images of sparrow

Step 3: Are images of sparrow birds captured by camera

No; Go back to step 2

Yes; Go to step 4

Step 4: Store captured images

Step 5: Were images of the sparrow enough?

No; Go to Step 6

Step 6: Download images of sparrow bird from the internet

Go back to step 4

Go back to step 5

Yes; Go to step 7

Step 7: Pre-process the sparrow images

Step 8: Combine the pre-processed images of the sparrow to form a dataset

Step 9: Dataset is stored in a folder called train

Step 10: Host the train folder on kaggle for easy and faster training of the model

Appendix III

<u>QUESTIONAIRE FOR RICE PRODUCTION AND CHALLENGES IN NENWE (Q20)</u>

<u>Please tick the correct answer in the space provided for each question</u>

(1) Name...
(2) Occupation is ....( )Farmer ( )Herder
(3) Are you a rice farmer? ( ) NO ( )YES
(4) Have you grown rice for over 20 years ( )YES ( ) NO
(5) What is the greatest problem facing rice production in your farm?
( ) Lack of Capital ( ) Bird infestation
(6) If the answer to question 5 is bird infestation, can you identify the particular bird causing harm in your farm?

( ) YES ( )NO

(7) What is the name of this harmful bird?...................................
(8) Are you doing anything to scare these harmful birds away from your farm? ( ) YES ( ) NO
(9) Is your method of scaring them working properly?
( ) NO ( ) YES
(10) Does this bird infestation affect your harvest negatively?
( ) YES ( ) NO
(11) Are these harmful birds the only birds that visit your farm?
( ) NO ( ) YES
(12) If the answer to question 11 is NO, do you then consider some birds as harmful while some others as harmless?
( ) NO ( )YES
(13) Do the harmful birds feed directly on the rice grains?
( ) NO ( ) YES
(14) Do the harmless birds feed directly on the rice grain?
( ) NO ( ) YES
(15) If your answer to question 14 is NO, have you taken time to study the harmless birds in your farm?
( ) NO ( ) YES
(16) What does the harmless bird do in the farm?
( ) Feeds on the rice grain ( ) Feeds on the small insects that attack the rice plant
(17) Do you want a solution to this problem of harmful bird infestation of your rice farm
( )NO ( )YES
(18) Can you give me access to your farm to carry out a research to solve this problem?
( )NO ( )YES
(19) What is the name of the predator for the harmful sparrow birds?.........................