Development of a Specie-specific Bird Deterrent System using Birds Classifications by Convolutional Neural Network (CNN) Model

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Abstract— *A trained convolutional neural network (CNN) model was developed in this work for classification of birds that visit rice farms into harmful Sparrows or beneficial insectivorous birds, and the classification used in activating efficient pest bird deterrence. Different images of the prevalent pest sparrow were captured by high resolution camera, and used as datasets for the training of the CNN model for the pest bird identification. Since, 98% of sparrow birds are grain eaters and harmful to a rice farm, 2,000 images of different sparrow birds were used together with the 419 different images of the prevalent Sparrows found in the rice farms as datasets for the training of the CNN model in Google Colab platform. A suitable algorithm was developed that uses this birds classification for recognizing the birds that visit the farm as pest Sparrows or otherwise. A bioacoustics deterrent system that uses the recorded sound of a local predator of Sparrows was developed for sparrow-pests. This sound was activated to broadcast the predator sound through the speakers to scare away the birds once Sparrows are sighted in a rice farm or nearby surroundings. However, if the sighted bird is recognized as not a Sparrow, no sound will be activated, so that the beneficial birds will be allowed do their biological insect-pest control in the rice farm. The algorithm can also be used by researchers and teachers in agriculture-related disciplines to teach bird classification in a rice farm.*

Keywords— Convolutional Neural Network, Bird Classifications, Sparrow-pests, Beneficial Birds, Integrated pest control, Rice Farm.

I. INTRODUCTION

Two thirds of the Nigerian populace get their livelihood from agriculture; a major source of income and feeding for most developing nations. Presently, it contributes well over a fifth of Nigeria's gross domestic product (GDP) [1]. Pest infestations in farms seem to be a major part of the numerous problems faced by the agricultural sector [1-8]. Birds are the most destructive pests to in crops farms, and total loss of farm produce can ensue if birds are not controlled [2]. While Java Sparrows are the most destructive bird pests for rice in the farm, there are other birds which feed on insects that attack the rice plants; thus performing biological pest control [2-7]. The different bird deterrent solutions available are not specific in the type of birds to be scared away and some do not deploy the right predator for such birds. With non-selective scaring away of birds, the pest-birds are scared away as well as some of the useful insectivorous birds. These insectivorous birds, by feeding on insects and other rice pests, effect biological control of the pest population; increasing the productivity of rice. Hence a device that can be used for detecting the harmful birds and scare them away while leaving the beneficial ones to remain in the farm will be a welcome development.

Unmanned Aerial Vehicles (UAVs) or drones has be used in capturing, processing, and analyzing images for farm pest management, but have limitations like untimely reach to remote spots, security-related ban, altitude reach limitation and scaring of harmful and useful birds alike [3]. Additional pollution, wind opposition and non-conservation issues arise when chemical deterrence is used with the drones [9]. Drones equipped with multispectral, thermal and visible cameras have been deployed for monitoring in agriculture, but challenges of drone architecture, wind influence on flight, low GPS accuracy have been reported [10]. Researchers [11] have been carried out land area estimation and classification with drone and satellite data via machine learning. Machine learning has also applied image recognition to vineyard and agricultural objects with 89.6% accuracy [12]. A bird repellent system based on bird features identification-image processing has been deployed with Raspberry pi, a sound speaker on rice farm [13]. The device utilized a model trained separately using Haar features, HOG (Histogram of Oriented Gradients) and LBP (Local Binary Patterns) and Python and Open CV library software. The system achieved 76% highest accuracy from Harr, 72% from LBP and 27% from HOG, but did not specify the particular birds to be repelled. Both pest birds and beneficial birds were scared away from the rice farm using the same sound. The cognitive abilities of birds make them to attach sounds to previous experiences. Those birds that have not had an ugly experience associated with such sound would return to the farm and may not be scared away by such sound again. This work could not guaranty increase in rice yield since both the harmful and beneficial birds would be scared away and the insect pests would attack the rice plant without any resistance.

CNN can learn highly abstracted features, especially spatial data [14] 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. Intermediate terms calculation avoidance are consequently enabled in the CNN [15], 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 backpropagation 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 for large image data storage, recognition and classifications. The Raspberry pi 2 is a device (Small Computer) that was used for the Sparrow bird image preprocessing and video streaming [16]. This research work aims at using artificial intelligence and machine learning to develop a convolutional neural network (CNN) model for classification of birds into harmful Sparrows or beneficial insectivorous birds. Such classification will be used to develop an efficient deterrent system for scaring of harmful sparrow-birds away from the rice farm using the sound of the predator of the Sparrow. This will make the birds to fly away from the rice farm since their cognitive abilities will match the predator sound with ugly experiences in the past.

II. MATERIALS AND DATA COLLECTION

2.1 Materials:

The materials used in the work are as follows:

2.1.1 Cameras:

These were strategically positioned in the farm to capture the different images of the sparrow-birds providing the much needed image datasets for the training of the convolutional neural network. High resolution digital 4K cameras were used. A Sparrow image captured by the camera is shown in Plate 1 and that of the different sparrow-birds obtained from different internet sources shown in Plate 2. These images were combined and preprocessed by Raspberry pi using python language to convert them into the Joint Photographic Group (JPG) image format and 3 dimensions (224, 224, 3) to form the dataset for the CNN training.

PLATE 1: Image of Sparrow bird captured in a Rice Farm

2.1.2 Raspberry pi 2:

This was used for the Sparrows image preprocessing and video streaming. It operated on Raspbian operating system; a version of Linux and a modified version of Debian. Python language was used.

2.1.3 Training Method:

Back-propagation (BP) training method was used. It reduced the volume of data (nodes) needed and the cost involved. This training was repeated until either the specified error rate was obtained or the number of training cycles (Epochs) was reached.

PLATE: 2: Images of Different Harmful Sparrow Birds from Other Locations (Source: Internet).

2.1.4 Python Language:

This was used to train the model in Google Colab platform for rice bird recognition and classifications.

2.2 Data Collection:

Data collection was divided into two stages:

1. The use of questionnaires to identify the most dangerous rice bird in the selected rice farms. In the course of this research, fifty rice farmers were interviewed and five rice farms were selected in Nenwe community of Aninri local

government area in Enugu state, Nigeria. The prevalent pest-birds for rice farms in Nenwe (6.1328°N, 7.5396°E) was identified using the questionnaires other vital information including the bird's local predator was also extracted.

2. Obtaining the different images of the selected rice farm and Sparrows with camera and download of more Sparrow images from the internet. The different images of the sparrow-birds and the selected rice farms were captured by the camera.

2.3 Development of the Proposed Deterrent System

The development of the proposed deterrent system is divided into 4 sub-headings as follows:

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

The data set for model training was generated from the algorithm in the Flowchart in Figure 1; derived from the steps below:

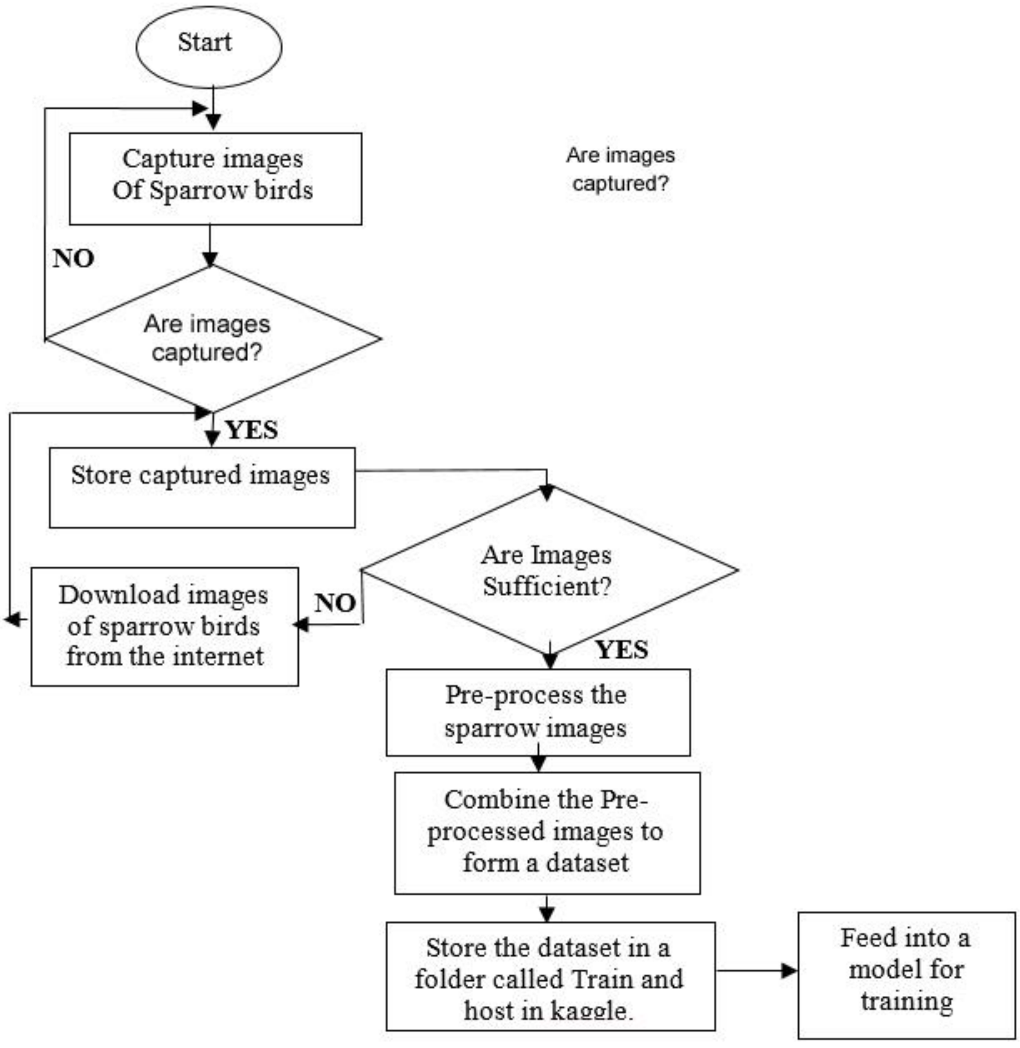


FIGURE 1: Flowchart for Building of Training Dataset

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: Are 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

2.3.2 Development of the CNN Model:

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. The model development algorithm is as in the steps below and as shown in the flow chart in Figure 2.

Step 1: Start

Step 2: Search for pre-trained model in tensor flow

Step 3: Is the EfficientNetB5 model found?

No; Go back to step 2

Yes; Go to step 4

Step 4: Download the efficientnetb5 pre-trained model

Step 5: Prepare a dataset for model training

Step 6: Is dataset prepared?

No; Go back to step 5

Yes; Go to Step 7

Step 7: Data verification

Step 8: Is data verified?

No; Go back to step 7

Yes; Go to Step 9

Step 9: Create convolutional base

Step 10: Freeze the pre-trained model's parameters

Step 11: Is the efficientnetb5 frozen?

No; Go back to step 10

Yes; Go to step 12

Step 12: Add dense layer on top of the frozen efficientnetb5

Step 13: Compile the model

Step 14: Train the Model

Step 15: Evaluate the Model

Step 16: Is the model efficient?

No; Go Step 17

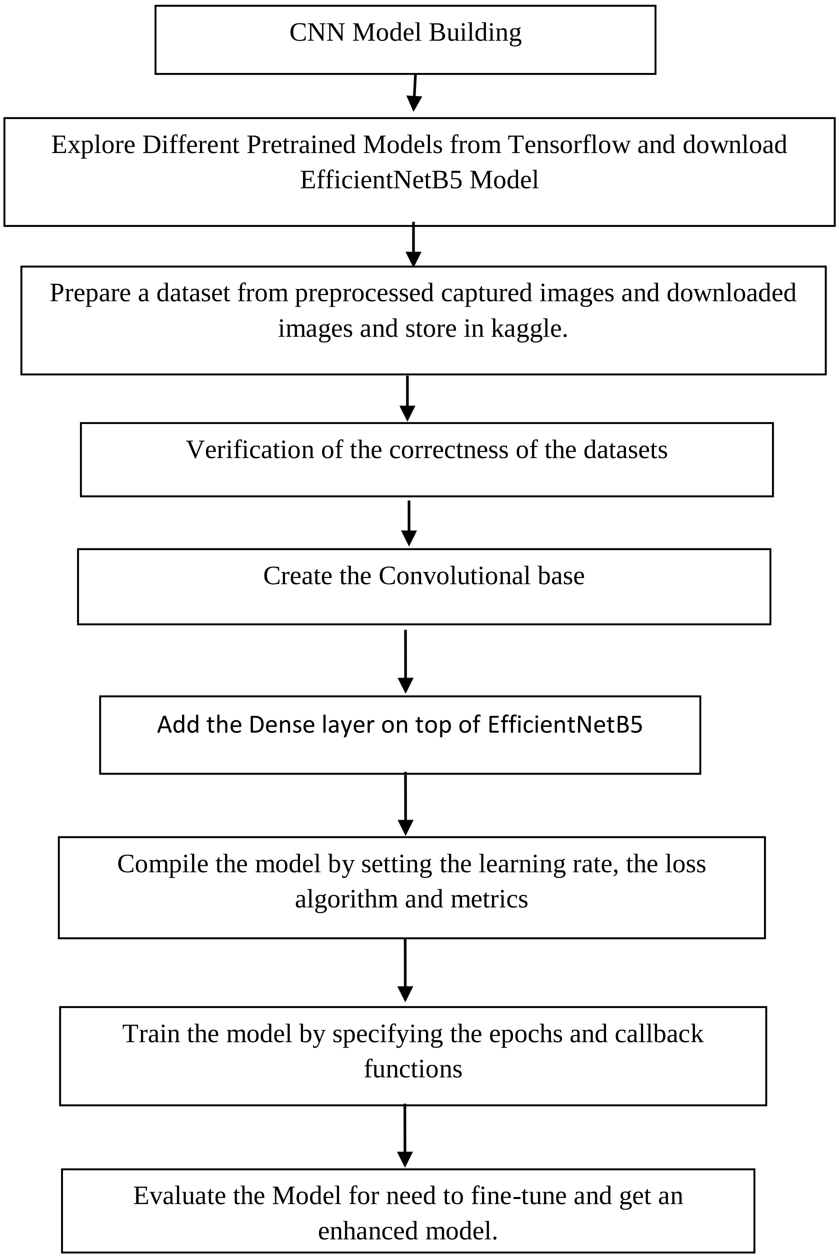


FIGURE 2: Building Block of a Convolutional Neural Network (CNN) Model

Step 17: Fine tune the model

Go back to step 14

Go to step 15

Go to step 16

Yes; Go to step 18

Step 18: Store the Model in Kaggle

Figure 3 shows the sequence of the enhanced 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 3: Enhanced CNN Model Showing Inputs and Output Layers with More Trainable Parameters

2.3.3 Training of the Developed CNN Model with Training Datasets

The developed model was trained with the dataset developed in section 2.1 to determine how well the model will be able to classify birds in the rice farm into harmful sparrow and beneficial birds. This training was carried out in Google Colab platform with epoch of 20 and 2419 preprocessed images of sparrow birds so as to obtain improved training and validation accuracies at highly reduced losses.

2.3.4 Development of an Efficient Algorithm for the deterrent System

The efficient algorithm for bird deterrent was developed using the developed algorithm as follows:

Step 1: Start

Step 2: Monitor the trained enhanced CNN model

Step 3: Is any sparrow bird identified by the model?

No; Go back to step 2

Yes; Go to step 4

Step 4: Classify the sparrow bird to identify the right predator

Step 5: Is the sparrow bird classified?

No; Go back to step 5

Yes; Go to step 6

Step 6: Simulate the predator sound on the speaker to scare away the bird

Go back to step 2.

The flow chart for the algorithm is presented in Figure 4.

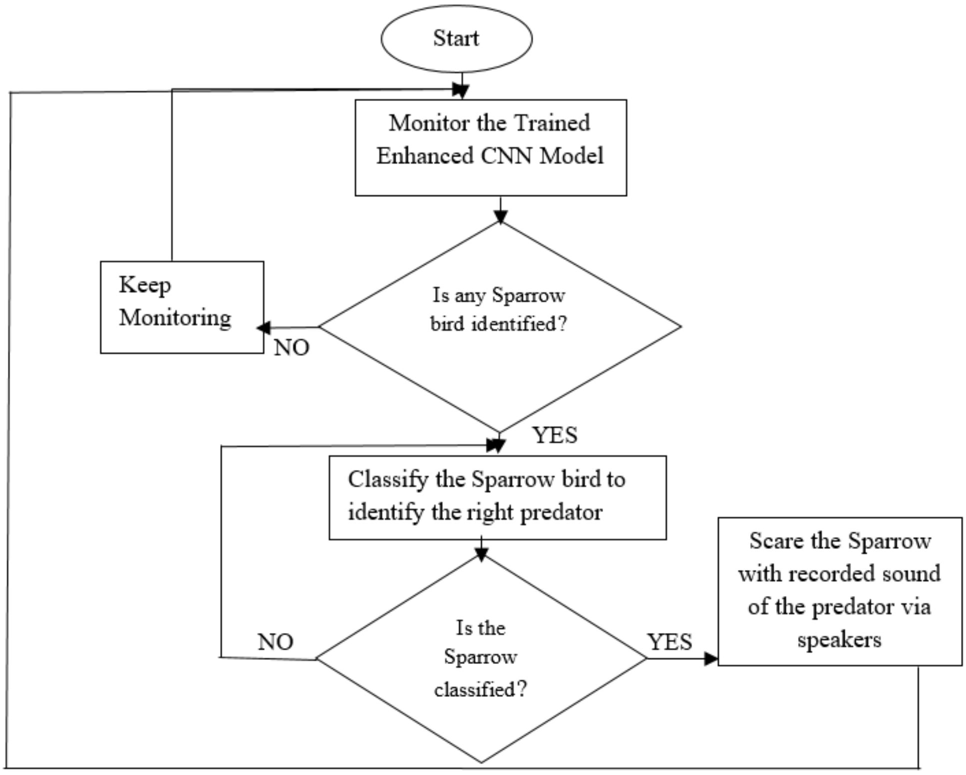
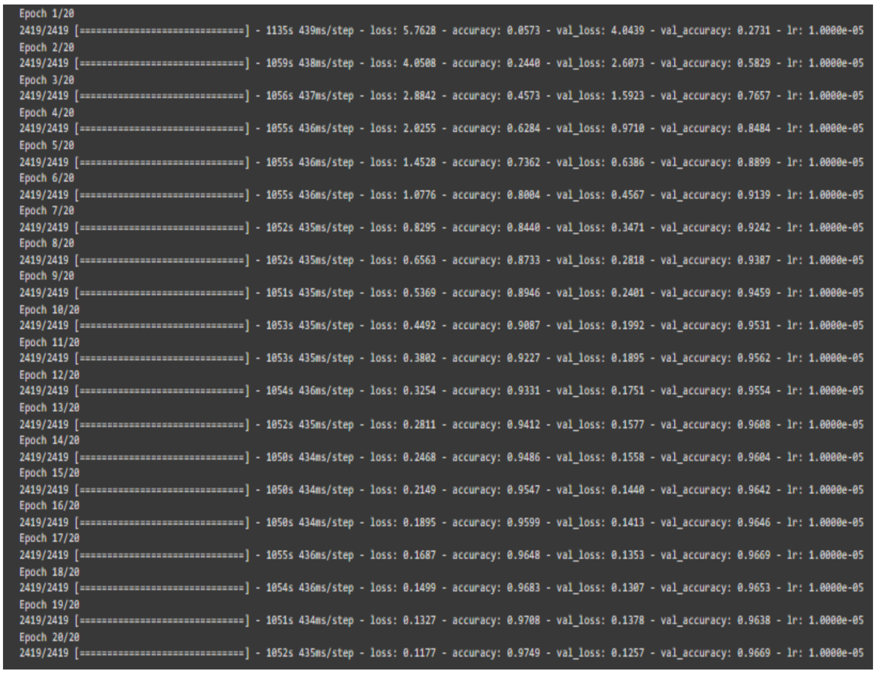


FIGURE 4: Flow Chart for Bird Deterrent

III. RESULTS AND DISCUSSION

3.1 CNN Training and Validation Accuracies and Losses

The result obtained from the training of the developed enhanced CNN model of Figure 3 for bird classification bird type found in the rice farms are shown in Figures 5 and 6 and also in Table 1. The losses decreased with increasing Epoch, while the accuracy increased with the increasing Epoch. This showed that the trained enhanced CNN model has a high likelihood of classifying the Sparrow images correctly.



```
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 5: Training Results of Developed Enhanced CNN Model for Bird Classifications in a Rice Farm with epoch=20

TABLE 1
TRAINING AND VALIDATION ACCURACIES AND LOSSES FOR THE ENHANCED 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 1, the developed enhanced CNN model for bird classification in a rice farm has increased number of trainable parameters as shown in Figure 3 which after the back-propagation training with a dataset of 2419 images of sparrow birds yielded very low training losses as shown in Figures 5 and 6. Also, the validation loss was small with high validation and training accuracy of 97% as also shown in Figures 5 and 6. Bird features identification-image processing studied by [13] obtained an accuracy of 76%.

This shows that 97 out of every 100 Sparrow images will be correctly classified while 3 will be classified wrongly. The gap between the training and validation losses narrowed as the epoch increased. The training and validation losses became equal at epoch of 20. Showing that 20 is the optimal epoch. Similarly, the difference between the training and validation accuracy reduced as the epoch increased and became zero at epoch of 19. This mean that best accuracy will be obtained a training Epoch of 19.

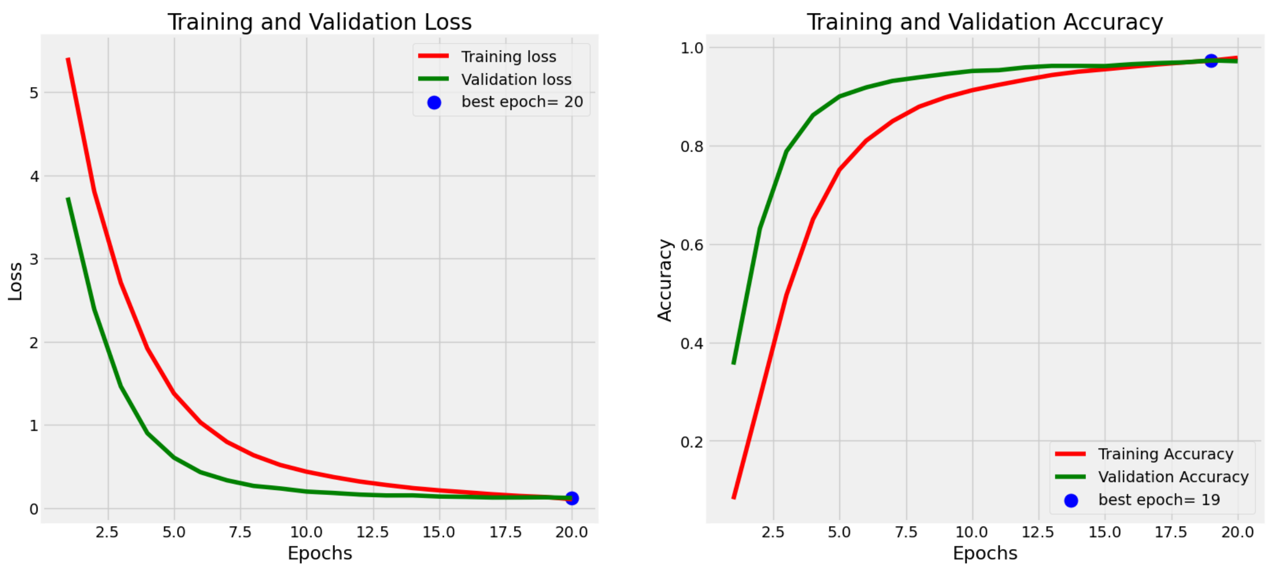


FIGURE 6: Training and Validation Accuracies and Losses of the Developed Enhanced CNN Model

3.2 Beneficial bird Classification in Google Colab Platform

FIGURE 7: Result of Beneficial Bird Classification in Google Colab

Figure 7 shows the result of the developed CNN model that classified a bird image fed into it as beneficial. The image of the bird was captured from a bird database called bird.cvs and the path name of the bird was copied and pasted into the prediction path name of google colab. The developed enhanced 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.

3.3 Result of Harmful bird Classification in Google Colab Platform

Figure 8 shows the result of the developed enhanced CNN model that classified a bird image fed into it as harmful. The image of the bird 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 enhanced 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 in the raspberry pi 2 or computer activates the speakers to produce the recorded sound of the predator (squirrel) which plays on the prediction window as shown in Figure 8.

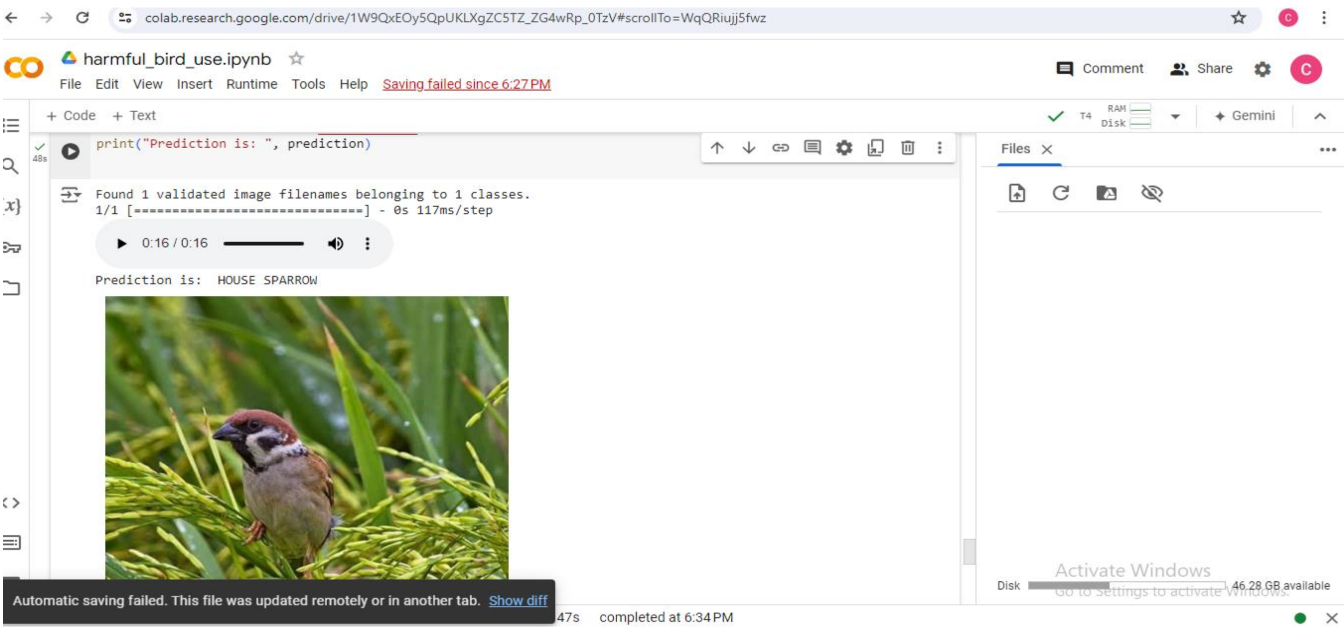


FIGURE 8: Result of Harmful bird Classification in Google Colab Platform

3.4 Results of Model Evaluation

Figure 9 shows the result of predictions of the model with True Positives, True Negatives, False Negatives and False Positives for 700 images predictions. Using the predictions shown in Figure 7, the parameters were obtained as follows:

$$Accuracy = \frac{280+400}{280+400+10+10} = 97.2\% \quad (1)$$

$$Precision = \frac{280}{280+10} = 96.5\% \quad (2)$$

$$\text{Recall} = \frac{280}{280+10} = 0.965 \quad (3)$$

$$F1\ Score = \frac{2\times0.965\times0.965}{0.965+0.965} = 0.965 \quad (4)$$

Thus 680 images of the 700 brought for recognition were correctly recognized. 280 sparrow images were truly recognized by the while 10 sparrow images were wrongly recognized as “not-sparrow”. 400 other birds’ images were correctly recognized as “not-sparrow”, while 10 other birds images were wrongly seen as Sparrow. This means that for every 100 Sparrows that approached the farm, the system will rightly activate the predator sound for approximately 88 and wrongly refrain from making a scaring sound for 12 Sparrows. Similarly if 100 other birds approached the farm, the system will rightly refrain from making a scaring sound for approximately 97 birds and wrongly activate the predator sound for 2.5 (approximately 3) of the birds. The system precision was 96.5%.

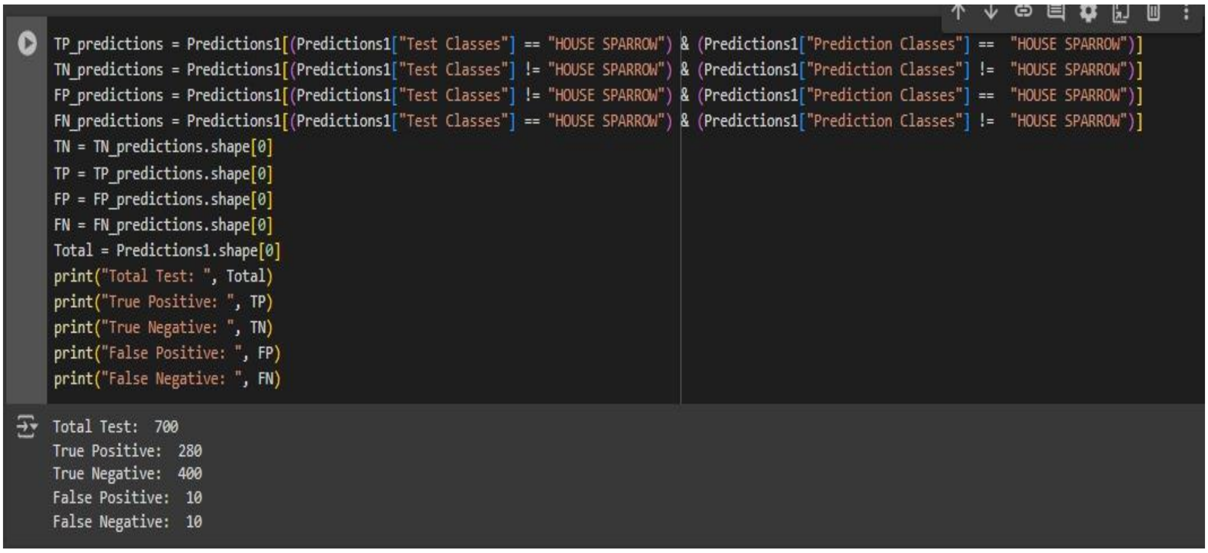


FIGURE 9: Results of Evaluation of the Model

IV. CONCLUSION

The developed Sparrow deterrent system used the bird classification into harmful sparrow and beneficial birds by the Convolutional neural network (CNN) model to scare away pest-sparrow bird using predator sound. When the model was used for predictions as shown in Figure 9, it was able to give high accuracy (97.2%), precision (96.5%), recall (0.965) and F1 score (0.965) of the model .Also in a Google Colab platform, the developed model was able to classify birds into harmful sparrow and beneficial (insectivorous) birds. It allowed the beneficial bird in 97% of their visits. Hence, it allowed the beneficial bird to continue its biological pest control without disturbances. However, when the model classification returned harmful Sparrow as shown in Figure 9, it generated the sound of Squirrel which is the predator 97% of the times to scare them away. This was better than the 76% accuracy birds’ classification obtained by a previous researcher [13].

REFERENCES

[1] Sasu, D. D. (2023). Share of GDP by agricultural sector in Nigeria 2023. https://www.statista.com/aboutus/our-research-commitment/2683/doris-dokua-sasu Site visited 20/05/2024.

[2] Montràs-Janer, T., Knape, J., Nilsson, L., Tombre, I.., Pärt, T. and Månsson, J. (2019). Relating National Levels of Crop Damage to the Abundance of Large Grazing Birds: Implications for Management.

[3] Abdullahi, H.S ., Mahieddine, F. & Sheriff, R.E (2015). Technology Impact on Agricultural Productivity: A Review of Precision Agriculture using Unmanned Aerial Vehicles (UAVs).
https//www.researchgate.net/publication/283641594. (20/12/2019).

[4] Ahmad, E., Hussain, I., Eds. (1990). Pakistan Agricultural Research Council. Islamabad, Pakistan: pp. 187–191.

[5] Alexander. M, Nicole .M and Daniel .T (2014). Prey Responses to Predator's Sounds: A Review and Empirical Study. California, Los Angeles USA: Department of Ecology and Evolutionary Biology, University of California, Los Angeles.

[6] Andelt, W.F.; Woolley, T.P.; Hopper, S.N. (1997). Effectiveness of Barriers, Pyrotechnics, Flashing Lights, and Scarey Man for Deterring HeronPredation on Fish. Wildl. Soc. Bull. 25, 686–694.

[7] Bahr, J.; Erwin, R.; Green, J.; Buckingham, J.; Peel, H. (1992). A Laboratory Assessment of Bird Responses to an Experimental Strobe Light Deterrent. Sidney, BC, Canada: The Delta Environmental Management Group Ltd. and Southwest Research Institute.

[8] Belton, P. (1976). Effects of Interrupted Light on Birds. Burnaby, Canada: Simon Fraser University.

[9] Beuter, K.J., Weiss, R. (1986). Properties of the Auditory System in Birds and the Effectiveness of Acoustic Scaring Signals. Copenhagen, Denmark: In Proceedings of the Bird Strike Committee Europe pp. 60–73.

[10] Blokpoel, H. (1980). Gull Problems in Ontario. Ottawa, ON, Canada: Canadian Wildlife Service.

[11] Swati, D., Swati, V.K., Shweta.S.G., Sayali, S.N. and Purva V.G (2015). Agricultural Drones for Spraying Fertilizers and Pesticides. International Journal of Advanced Research in Computer Science and Software Engineering. 5(2), 804-811.
www.ijarcsse.com

[12] Hafeez, A., Husain, M. A., Singh, S. P., Chuaha, A., Khan, M. T., Kumar, N., Chuahan, A.Soni, S. K. (2023). Implementation of drone technology for farm monitoring and pesticide spraying: a review. Information Processing in Agriculture. 10 (2), 192-203. Doi:10.1016/j.inpa.2022.02.002

[13] Deepak, M., Akanksha, G., Tasneem, A., & Dharmendra, S. (2017). Fusion of Drone and Satellite Data for Precision Agriculture Monitoring. Published in: 2016 11th International Conference on Industrial and Information Systems (ICIIS) Roorkee, India, Date of Conference: 3-4 Dec, 2016. DOI: 10.1109/ICIINFS.2016.8263068.

[14] Bongiovanni R, and Lowenberg-Deboer J. (2004). Precision Agriculture and Sustainability. Kluwer Academic Publishers.

[15] Oluwole, A., Adefemi, A. and Ade-Omowaye, J. (2020). Oluwole, A., Adefemi, A. and Ade-Omowaye, J. (2020). A Real Time Image Repellent System Using Raspberry pi. FUOYE Journal of Engineering and Technology, vol.5,Issue 2, September 2020.

[16] Ghosh, A., Sufian, A., Sultana, F., Chakrabarti, A. and De, D. (2020). Fundamental concepts of convolutional neural network. Recent Trends and Advances in Artificial Intelligence and Internet of Things doi: 10.1007/978-3-030-32644-9_36

[17] Vakalopoulou, M., Christodoulidis, S., Burgos, N., Colliot, O. and Lepetit, V. (2023). Deep learning: basics and convolutional neural networks (CNN). Colliot, O. (Ed) Machine Learning for Brain Disorders, Springer, 2023: 77-115. doi: 10.1007/978-1-0716-3195-9_3 . hal-03957224v2

[18] Oludare, I.A., Aman, J., Abiodun, E.O., Kemi, V.D., Nachaat, A. M., and Humaira, A. (2018). State-of –the-art in artificial neural network applications: A survey. ELSEVIER Heliyon, 13 November 2018. DOI: 10.1016/j.heliyon.2018.e00938.