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A CONVOLUTIONAL NEURAL NETWORK MODEL FOR HARMFUL BIRDS RECOGNITION AND DETERRENT IN A DYNAMIC RICE FARM ASSOCIATED WITH BIRD MIGRATION AND CLIMATE CHANGES.

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Abstract: **This paper presents the development of a convolutional neural network (CNN) model for harmful bird recognition and deterrent in a dynamic rice farm associated with bird migration and climate change. In this research work, the prevalent harmful sparrow bird was identified and the different images of the bird were captured by high resolution camera to form part of the datasets for the training of the CNN model. However, to ensure the reliability of the CNN model developed over time, the dynamic rice environment due to bird migration and climate change has to be considered while training the CNN model. Since, 98% of sparrow birds are grain eaters and harmful to a rice farm, 85,000 images of different sparrow birds across the globe were used together with the different images of the prevalent sparrow birds in the rice farm as datasets for the training of the CNN model in Google Colab platform. The CNN model classifies the birds into harmful sparrow and beneficial birds. An algorithm was developed to use the classification of the CNN model to generate the recorded predator sound to scare away the harmful sparrow bird that migrates into the farm from any region since 85, 000 different images of sparrow and the captured images of the sparrow in the rice farm were used as the training dataset for the CNN model. Also, the predators for the sparrows are classified as Squirrel and Hawk. Hence, once a sparrow is active in the rice farm and detected by the trained CNN model, the appropriate predator sound is simulated through the speaker to scare away the particular sparrow bird. Hence, this CNN model was developed and trained to deal with dynamic rice farm associated with bird migration, climate change or any other biotic and abiotic factors that may cause changes in the bird migration and population in the farm.**

Key Words: **Convolutional Neural Network(CNN), Dynamic Rice Farm, Climate Change, Bird Migration, Bird Deterrent.**

I.INTRODUCTION

Agriculture is a major source of income and feeding for most developing nations. Presently, it contributes well over a quarter of the gross domestic product (GDP) in Nigeria and two- thirds of the populace depends on it for their source of livelihood. Of the numerous problems faced by the sector, the major seems to be of pest infestations in farms[1]. Pests are broadly classified as harmful organisms (Plants and Animals) that cause harm to people, their food or environment. Birds are the most destructive to farm crops[2-6]. Theyalso cause total loss of farm produce if no control systems are available. Birds are the most destructive to farm crops and birds like Java Sparrow are the most destructive bird pests for rice This research work was carried out to ensure the use of artificial neural network to model a bird deterrent in a dynamic rice farm considering bird migration and climatic change. After careful observation of the different bird deterrent solutions in a rice farm, it was discovered that most of them are not specific in the type of birds to be scared away and the right predator for such birds. Going by this research, it was discovered that in the process of scaring away the birds, some vital insectivorous birds are also scared away. These insectivorous birds are supposed to feed on insects and other rice pests as a biological means of controlling the pest population thereby increasing the productivity of rice. To

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model a rice farm properly, some dynamics like bird migration and climate changes should be considered.

II. DYNAMIC RICE FARM

In reality, a rice farm should be treated as a dynamic entity due to factors like bird migration and climate change. In modeling a rice farm to identify the prevalent harmful sparrow birds present in the rice farm, the farm should be seen as a dynamic entity whose parameters are likely to change with time. Due to climate change and bird migration, the prevalent harmful sparrow birds in a rice farm may disappear after a decade while new sparrow species may migrate to the rice farm. Hence, during training of the CNN model, the model was trained with different images of the present prevalent harmful sparrow birds and about 85,000 images of different sparrow birds across the globe. This made the model to remain relevant in a dynamic rice environment due to climate change and bird migration [5-15].

III MATERIALS AND METHOD

These 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.

3.1 Hardware Materials

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

(a) Cameras

These are the devices strategically positioned in the farm to capture the different images of the sparrow birds. They provided the much needed image data sets for the training of the convolutional neural network.

Plate 3.1: High Resolution Digital 4K Camera

Plate 3.2: Image of Sparrow bird captured in a Rice Farm

The image in plate 3.2 was captured by the digital 4k camera in plate 3.1. Similarly, the different sparrow birds' images in plate 3.3 were obtained from different internet sources and they are combined with the different images as captured in plate 3.2 by camera in plate 3.1. These combined sparrow birds' images are 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) to form the dataset for the training of the Convolutional neural network (CNN).

Plate: 3.3: Images of Different Harmful Sparrow Birds From Other Locations (Source: internet).

Table 3.1: Deployments of Cameras Based on the Size of the Rice Farm

Table 3.1 shows the number of cameras and the locations in a rice farm based on the size of the rice farm.

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
Above 1500 to 3000	Above 160 to 220	60 Degrees	37	6
Above 3000 to 6000	Above 220 to 320	45 Degrees	40	8
Above 6000 to 12000 hec	Above 320 to 440	30 Degrees	37	12

Table 3.1 was derived using equations 3.1 and 3.2 and these equations can be used to determine the number of cameras, relative angle of deployment and the separation distance of the cameras based on the dimension of the rice farm.

$$\text{No of Cameras} = \frac{360}{\text{Relative Angle of Deployment}} \quad . \tag{3.1}$$

$$\text{Separation Distance of Camera} = \frac{\text{Perimeter of Rice Farm}}{\text{No of Cameras}} \tag{3.2}$$

The cameras were deployed in such a way as to cover the 360 degree overview of the rice farm. Since, most agricultural lands are measured in hectare.

$$1\text{hectare} = 10{,}000 \text{ meter square} \tag{3.3}$$

(b) Raspberry pi 2

The Raspberry pi 2 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.

(c)Speakers

They were used to produce the simulated sound of the squirrel (Predator) which scared the harmful sparrow birds away from the rice farm.

$$\text{No of Speakers} = \frac{360}{\text{Relative Angle of Deployment of Cameras}} \quad . \tag{3.4}$$

$$\text{Separation Distance of Speakers} = \frac{\text{Perimeter of Rice Farm}}{\text{No of Speakers}} \tag{3.5}$$

Table 3.2: Deployments of Speakers Based on the Size of the Rice Farm

Area of Rice Farm (Square Meter)	**Perimeter Of Rice Farm (Meters)**	**Separation Distance of the Speakers (Meters)**	**Number of Speakers**
1500	160	40	4
Above 1500 to 3000	Above 160 to 220	37	6
Above 3000 to 6000	Above 220 to 320	40	8
Above 6000 to 12000 (1 hectare)	Above 320 to 440	37	12
Above 12000 to 24000 (2 hectares)	Above 440 to 640	40	16
Above 24000 to 48000 (4 hectares)	Above 640 to 880	37	24
Above 48000 (from 5 hectares and above	Above 880	27	48

3.2 Software Materials

These are programmes and software deployed in the realization of the objectives of this research work. Some of the software materials are discussed below.

(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.

(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.

IV DEVELOPMENT OF THE CNN MODEL

4.1 Enhanced Convolutional Neural Network (CNN) Model for Dynamic Rice Farm

Due to the dynamic nature of a real rice farm as a result of issues like bird migration and climate changes, for a model to remain relevant overtime there is need to train the model with so many bird images. Hence, this model was trained with a dataset that contains different images of the captured sparrow birds in the rice farm and 85,000 images of sparrow birds captured across the globe from internet as shown in plate 3.3.

Figure 4.1 shows the convolutional neural network (CNN) model with the different layers.

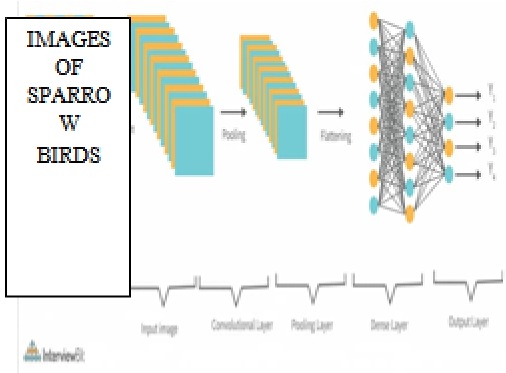

Figure 4.1: Convolutional Neural Network (CNN) [15].

4.2 Development of the Convolutional neural network (CNN) Model

In the development of this enhanced convolutional neural network (CNN), a pre-trained high efficient model called efficientnetb5 was frozen of its weights 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 sequence and blockare shown in figures 4.2 and 4.3 respectively..

```
 Layer (type)                Output Shape              Param #
=================================================================
 inputLayer (InputLayer)     [(None, 224, 224, 3)]     0

 AugmentationLayer (Sequent  (None, None, None, None   0
 ial)                        )

 efficientnetb5 (Functional  (None, 2048)              28513527
 )

 dense_3 (Dense)             (None, 1024)              2098176

 activation_2 (Activation)   (None, 1024)              0

 batch_normalization_2 (Bat  (None, 1024)              4096
 chNormalization)

 dropout_2 (Dropout)         (None, 1024)              0

 dense_4 (Dense)             (None, 512)               524800

 activation_3 (Activation)   (None, 512)               0

 batch_normalization_3 (Bat  (None, 512)               2048
 chNormalization)

 dropout_3 (Dropout)         (None, 512)               0

 dense_5 (Dense)             (None, 525)               269325

 activationLayer (Activatio  (None, 525)               0
 n)

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

Figure 4.2: Enhanced CNN Model Showing Inputs and Output Layers with More Trainable Parameters

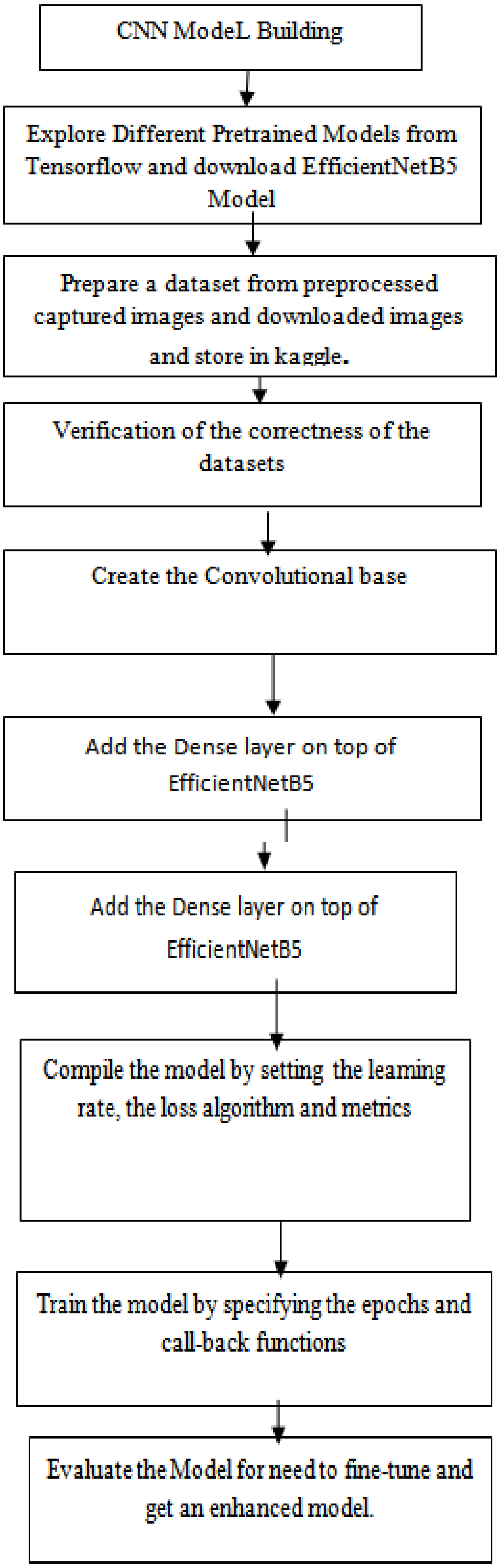

Figure 4.3: Building Block of a Convolutional Neural Network (CNN) Model

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 mode is shown in figure 4.2**V Results**

In figure 5.1, the developed enhanced CNN model for dynamic rice farm was trained with a dataset of 85,000 different images of Sparrow birds across the globe and different images of the captured sparrow birds in the rice farm and the training results were obtained and shown in figure 5.1 and table5.1.

```
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 5.1: Results of Training of Developed Enhanced CNN Model for Dynamic Rice Farm with epoch=20 using 85,000 images of Sparrow birds.

Table 5.1: 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
	0.4573	2.8842	0.7657	1.5923

3/20				
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 5.1, the developed enhanced CNN model for dynamic rice farm has increased number of trainable parameters as shown in figure 4.2 which after the training with dataset of over 85,000 images of sparrow birds yielded very low training losses as shown in figures 5.1 and 5.2. Also, the validation loss was small with high validation and training accuracy of 97% as also shown in figures 5.1 and 5.2. 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. This training with 85,000 images of sparrow birds will make the model to accommodate dynamics of bird migration and climate change associated with a rice farm and remains effective in the presence of such dynamics. Figure 5.3 is a google colab platform that shows the recognition of a sparrow bird by the CNN model developed and subsequent generation of predator sound by the algorithm developed for the monitoring of the CNN model's classification of birds to either harmful sparrow or beneficial birds.

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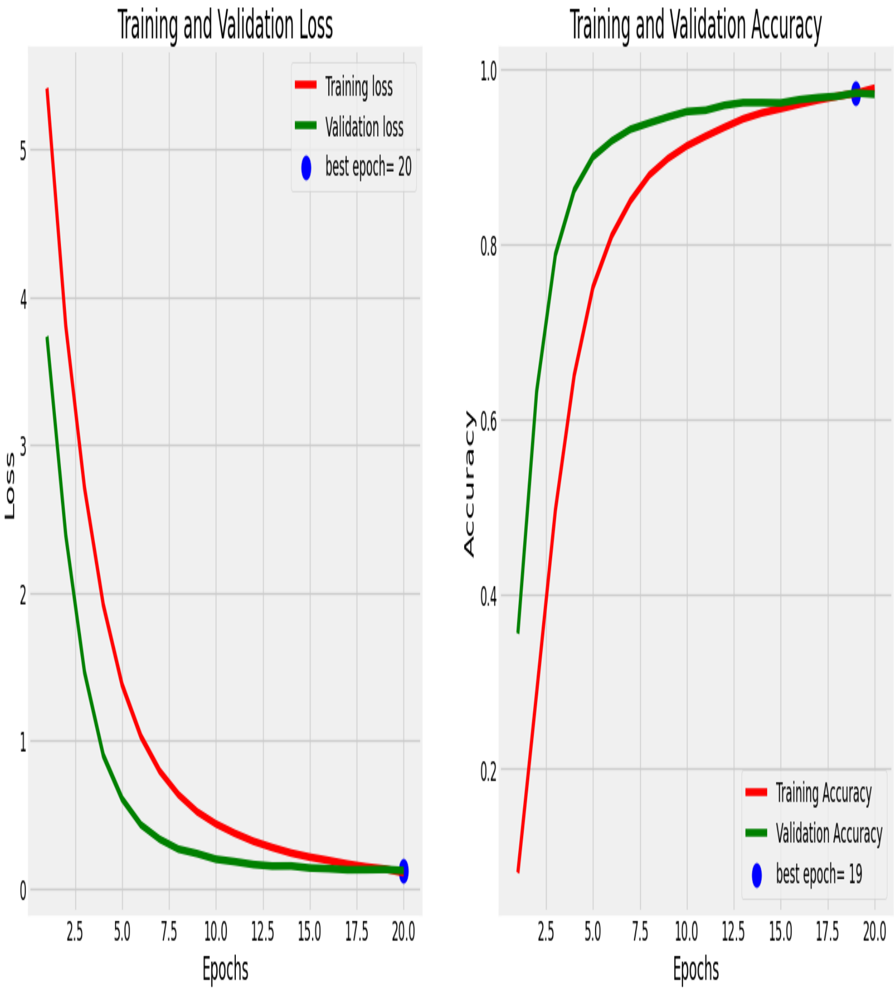

Figure 5.2: Training and Validation Accuracies and Losses of the Developed Enhanced CNN Model

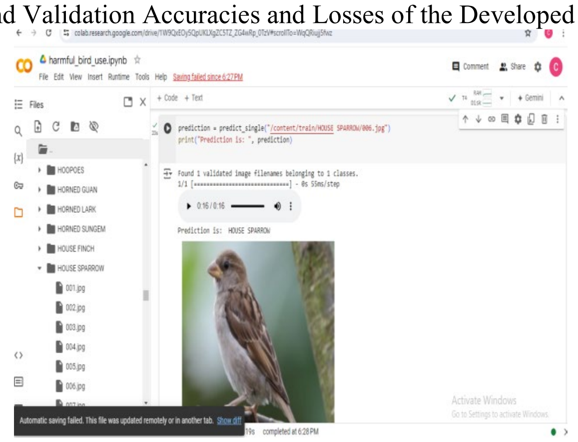

Figure 5.3: Google colab platform showing recognition and deterrent of sparrow bird using predator sound

VI CONCLUSION

This enhanced Convolutional neural network (CNN) modelwas used to model a dynamic rice farm to detect and deter the harmful sparrow birds over a reasonable length of years by taking into considerations some dynamics like bird migration and climate changes. The farm dynamics were taken care of by training the enhanced convolutional neural network(CNN) model with over 85,000 images of sparrow birds across the globe and within the farm.

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