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ORIGINAL RESEARCH

Animal Intrusion Detection using Deep Learning and Transfer Learning Approaches

Vidhyalatha T. Y Sreeraman . E Purushotham

Department of Computer Science and Engineering
Sreenivasa institute of technology and management studies, Chittoor, India.

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Abstract – One of the major risks to decreasing the harvest yield is crop damage caused by monster attacks. Crop attacking is one of the most aggravating conflicts between tamed and untamed life as a result of the expansion of developed land into former natural life habitat. India's ranchers are in grave risk from pests, natural calamities, and animal attacks that reduce production. Employing gatekeepers to keep an eye on crops and deter wild animals is not a practicable solution, contrary to conventional wisdom used by ranchers. Since the safety of both humans and animals is crucial, it is essential to protect the crops from animal-caused damage and to reroute the animal with little chance of mischief. In order to overcome these problems and get to our point, we employ artificial intelligence (AI) to detect animals as they enter our ranch using a division of computer vision known as a deep brain network. This paper promotes the ability to identify organisms in the natural world. Since there are so many different types of species, it might be difficult to physically discern between them. This algorithm organises animals based on their images so that we may more effectively filter them. In this paper, we will use a camera to take daily pictures of the surrounding area while simultaneously seeing the entire ranch at regular intervals. With the aid of sophisticated learning models, we can recognise the movement of creatures and play the appropriate sounds to scare them away. The various convolutional brain network libraries and concepts used to create the model are identified in this Paper.

Index Terms – Animal Intrusion Detection, Deep Learning, Transfer Learning, Image processing, CNN, VGG-16, VGG-19, and MobileNet.

I. INTRODUCTION

Because of deforestation, a lack of consistent prey, and environmental disaster, wild animals must now coexist closely with human settlements and hunt domesticated animals. Therefore, animals started hunting humans for food. In India, the elephant population is engaged in horrific conflict and is held accountable for the murder of living beings. People started destroying the wilderness for their way of life as a result of the conflict between humans and other animals and the population growth; this affected the animals and their homes. The rapid industrialisation of wooded areas led to the introduction of creatures

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into nearby settlements.They claim to hunt for crops, domesticated animals, occasionally humans, and cultivable terrain as a result of resource loss and drought. Ranchers typically employ electrical walls to protect their fields from animals that might shock themselves and respond in unexpected ways. Security for both humans and animals is very important. A sharp checking system that can screen naturally, recognise a picture of a creature portion, and alert people is needed to solve this problem. This overview study relies on many wired and remote applications that protect humans from interruption by other creatures. Research on the processing of organisms in images has been a key area for many applications [6]. IoT (Internet of Things) has evolved into a brand-new means of communication across the globe. It equips the capacities with a huge variety of uses, some of which are already relevant to our general public.

The destruction of agricultural produce by wild animals is one of the major societal challenges that now affects farming. The disruption of wild animals by wild animals has always been a problem for ranchers. Deer, wild hogs, moles, elephants, monkeys, and other animals are a few that pose a threat to the harvest. These animals may consume crops, wander around the field undetected by the rancher, and then ruin those harvests. As a result, the yield may suffer a great loss, and additional financial security will be needed to deal with the damage. When utilising his invention, each farmer should be aware that animals are also present in the area and that they need to be protected from any possible suffering. An immediate solution should be found to this problem, along with a strong arrangement. As a result, our paper hopes to find a solution to this problem. The Papers major goal is to keep wild animals away from agricultural fields while also protecting them by scaring them away rather than killing them. Additionally, the organisation seeks to safeguard people against animal assaults. To safeguard crops against animal assaults, we are employing an integrated approach in the field of deep learning to develop a monitoring and deterrent system.

II. RELATED WORK

This article reviews a few recent works on animal infiltration detection and identifies their flaws.

In order to prevent agricultural losses, and Salish et al. [6] both describe techniques to perceive elephant encroachment. According on the amount of activated vibration sensors, a camera trap takes a picture, and Latest API is used to determine whether amonster is around, according to Suganthi et al. Sailesh and colleagues utilise a camera attached to a Raspberry Pi device that continually takes pictures and looks to see if any of them have elephants in them. Both techniques include deterrents that may be used to keep elephants away, such as playing noises or turning on strong lights. Manifold Inactive Infrared sensors are used by Pooja et al. [2] and Pragma et al. [16] to detect the presence of wild animals. While Pragma et al. utilizesignaldiscovery as part of a camera trap and compare the acquired photos to a pre-populated database to identify the type of animal, Poojas et al. use the number of motion sensors activated as an indicator to the size of the animal, and hence its type. Based on the type of animal spotted, both systems are capable of performing various actions. To prevent animals from entering farms further, this might involve playing various noises, flashing lights, or even misting aerosol solutions.

The intrusion detection system that comes closest in design to the approach outlined in this study is presented by Agadir et al. [1]. Convolutional Neural Networks (CNNs) for object recognition are used

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in camera traps to capture images when movement is detected and to identify animals. For object recognition, the SSD model [14] is used, and if any wild animals are discovered in the image, an alert message is given to the owner instructing them to take the necessary action. A Raspberry Pi computer, situated in the same spot as the camera trap, handles all processing.

Using a mix of AIR (Active Infrared) and PIR sensors, the Animal Intrusion and Detection System (ANIDERS) [5] helps farmers reduce crop loss by detecting and preventing animal invasions. Alarms are activated upon detection to deter attackers. According to the WWF-India3 pilot research, the system correctly identified the animal 368 times out of the 539 catches that were within the ANIDERS' range, implying an accuracy of almost 68%. In this area, opportunity exists for improvement. Every option examined has a number of drawbacks. Most importantly, systems designed to detect animal intrusions must guarantee accurate species identification. Animals respond to stimuli differently; for example, a wild boar may be scared away by loud noises, yet an elephant may be startled and go on the attack.

To ensure fewer false positives, it is vital to identify the animal in addition to determining its intentions before sending out notifications. Furthermore, it is unknown how frequently these devices may provide false warnings. It's also unclear whether the systems can inform the user whether deterring the animal was successful once an alarm sounds. In addition to counting the number of animals, it would be helpful to determine the animal's last known location and its direction of travel in the event that numerous animals were found. All of this must be carried out in real-time or very close to it. Small computing units, such embedded systems, which can be installed on site, would need to be employed because the solution also has to be economical. All of these issues are attempted to be resolved by the solution suggested in this article, and an overview of the design is provided in the next part.

III. PROPOSED WORK

The invasion of wild animals into private land and in road crossings has been discussed several times in the India Times [5]. The major goal in these circumstances is to automatically drive away wild creatures without endangering human or animal life. The suggested technique overcomes these challenges since it merely requires routine software code maintenance, unlike manual methods that demand labor and systems with hardware to identify animals that require repair periodically. The idea of Deep Learning (DL) with Convolutional Neural Network (CNN) approach allows for the detection of wild animals when they are photographed by a camera. We can see our proposed work architecture in fig 1. The right repellant noises can be played in order to immediately scare away any animals that are identified.

Deep Learning Approach

Given that the aforementioned issue is still there despite all efforts, we used deep learning to autonomously drive the animals away. In our paper, we made use of tools like Keras and tensorflow to do the necessary preprocessing steps and provide a suitable output based on the model's identified output. Here, the code processes and predicts the frames received from the camera, and the appropriate animal-repelling sound is played to frighten the detected animal away. The input is coming from the CCTV (Closed Circuit Television) system.

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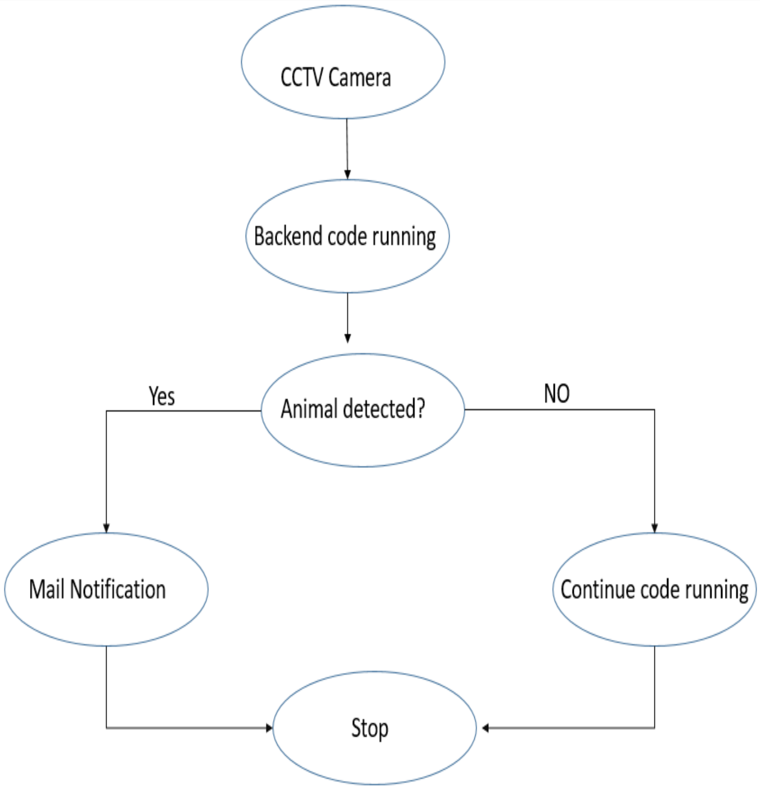

FIG. 1: PROPOSED WORK ARCHITECTURE

Dataset

Our model was trained using an image dataset. We manually gathered data on 10 distinct animal species. Giraffe, Deer, 500 Camel, 500 Cow, 500 Rabbit, 500 Pig, 500 Horse, 500 Monkey, 500 Tiger, and 500 Elephant are among the ten classes that are taken into account since we see these creatures as a threat to Indian agriculture and human life. The dataset is separated into two groups: training data and testing data.

Image Processing

In this case we collected 10 different class images and create 10 folders with class names save all the images into that respective folder. We need to read the images using that entire path and extract the class name also using that folder name. Using 'os.walkdir' get the images path and read the images using opencv and using split function extract the class names also. While collecting the datamanually we get driftnet pixel images but models won't accept different pixels. After reading the images convert the images into then reshape all the images into particular shape. Then we have class labels in object format need to convert into numerical used Label Encoder to convert the categorical data numerical data and split the data 70% train and 30% test data.

CNN model

After completed the image processing and data splitting directly send the data to the model before that need to define CNN architecture. First import model sequential then input layer in this layer fix the input shape images and give the activate function also. Then add input layer there just add 32 filter and (5,5) kerner size, Maxpoling and dropouts. This dropout is help our model to avoid overfitting. Again added two input layers with 64 and 128 filters, 5,5kernel size, same maxpooling and drop outs with Relu activation function. Default we useRelu only because if we use Tanh or Sigmod we will get some vanishing gradient problem to avoid this problem we use Relu activation function. Flatten the data and add dense layers with RELU activation only and finally defined the output layer with softmax activation. In this output layer we defined total how many classes are there also. Finally model building completed then compile it. In this compile stage have to define loss and performance metric and optimizer. IN this case we are working on multi class classification problem so we use categorical_crossentropy as loss function and accuracy as metric. Based on accuracy and loss we can decide the best model. After fit the model we get accuracy per each epoch. Plot confusion metric to confirm the result and check which class is going to miss classified or correctly classified.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 224, 224, 32)	2432
conv2d_1 (Conv2D)	(None, 224, 224, 32)	25632
max_pooling2d (MaxPooling2D)	(None, 112, 112, 32)	0
dropout (Dropout)	(None, 112, 112, 32)	0
conv2d_2 (Conv2D)	(None, 112, 112, 64)	18496
conv2d_3 (Conv2D)	(None, 112, 112, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 56, 56, 64)	0
dropout_1 (Dropout)	(None, 56, 56, 64)	0
conv2d_4 (Conv2D)	(None, 56, 56, 128)	73856
conv2d_5 (Conv2D)	(None, 56, 56, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 28, 28, 128)	0
dropout_2 (Dropout)	(None, 28, 28, 128)	0
global_max_pooling2d (Global	(None, 128)	0
dense (Dense)	(None, 256)	33024
dropout_3 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 10)	2570

Total params: 340,522
Trainable params: 340,522
Non-trainable params: 0

FIG. 2: PROPOSED CNN MODEL SUMMARY

Transfer learning models

We are trying transfer learningby using this we can predict very accurately. In CNN we define our architecture like input layers and dense layer but transfer learning no need to define anything that is already trained on large number of data set just change input layer and out layer and retrain it on our custom data. We tried VGG-16, VGG-19, and MobileNet. In this case we download pertained VGG16 model form keras.applications.vgg16 and change the input layer and output layer only. After importing download the vgg16 weight with our input shape (224,224,3) then declare output layer. Finally compile and fit the model predict the accuracy. VGG-19 model also same as vgg16 import download the weights and define the output layer based on number class and compile it. MobileNet model import from keras.applications.mobilenet and download the weights using this library only. Compile the model and fit it with categorical_crossentropy as loss and accuracy as metric. After training all these three models plot the accuracy, loss plot per each class and confusion metric also.

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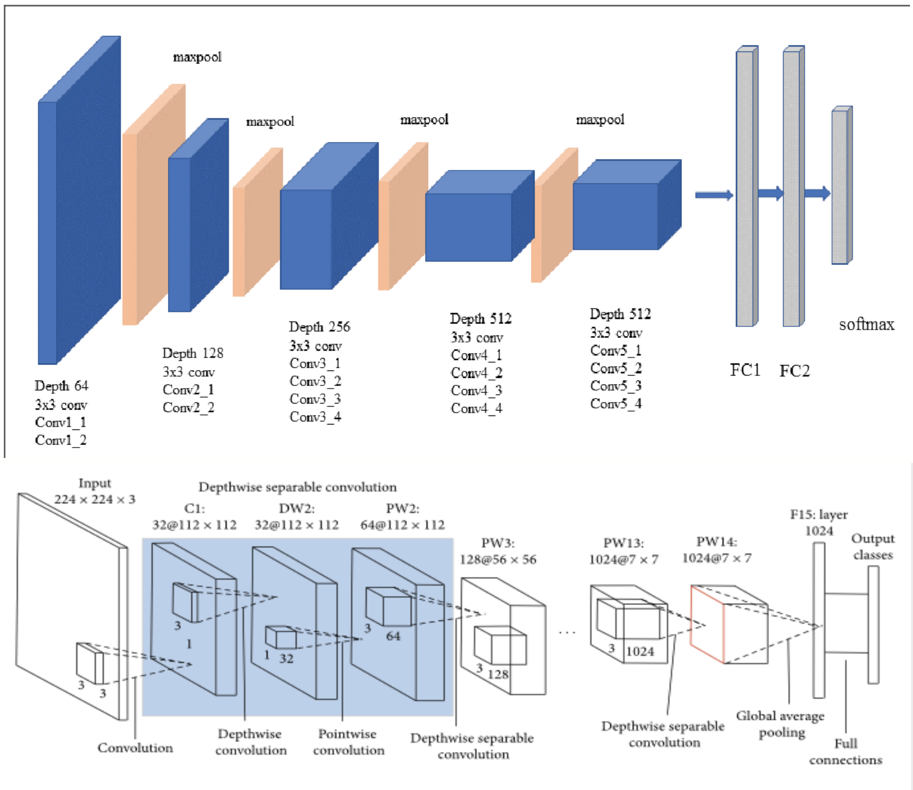

FIG. 3: MOBILE NET ARCHITECTURE

IV. RESULTS AND DISCUSSIONS

Thus, the proposed model will train the image dataset of monkey, boar and elephant by establishing Convolutional Neural Network and transfer learning models. To compare the trained photos with the fresh test images from the live capture, the stored model will be executed on the driver code. Using speakers, a repulsive sound is produced if one of the trained animals is found during the live capture in order to scare it away. Different test photos are provided, and their classes are recognised to verify the model's accuracy.

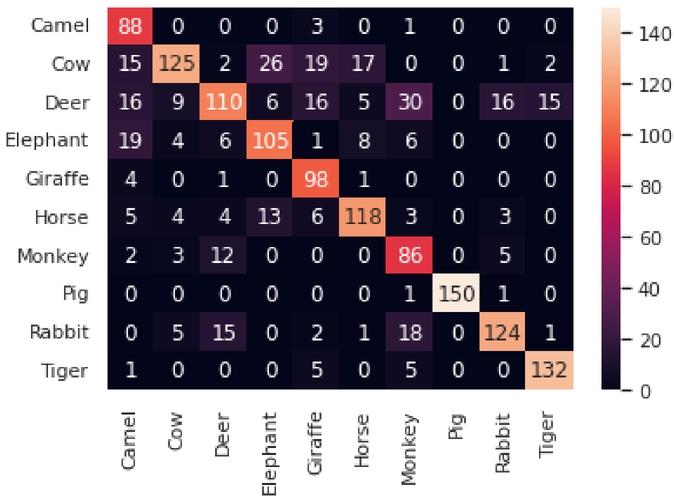

FIG. 4: CNN MODEL CONFUSION METRIC PLOT.

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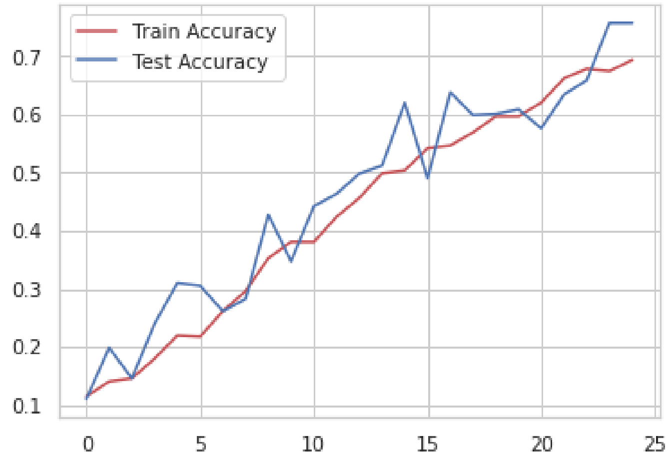

FIG. 5: CNN MODEL TRAIN AND TEST ACCURACY PLOT PER EACH EPOCH

By using CNN got 75% accuracy we can check it from confusion metric also. Seeing this confusion matrix which class images are correctly classified and which class images Missclassified we can identify easily. Seeing fig 4 some camel images classified into cow, deer and elephant and some deer images classify into monkey and rabbit. These all are the miss classified data points. We need to decrease these miss classified data points in fig 5 we can see train and test data accuracy each class.

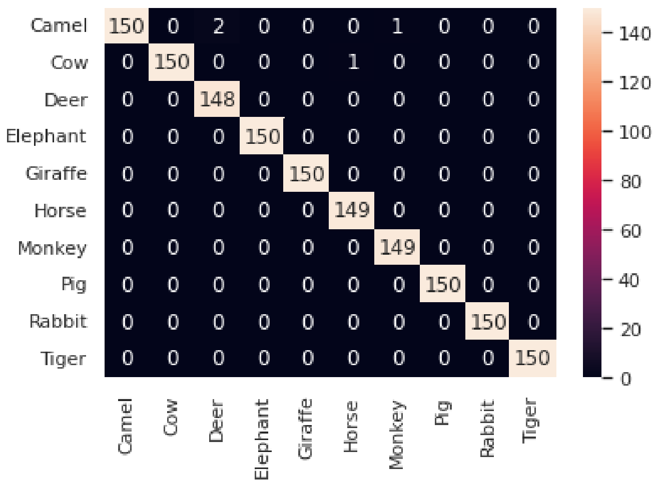

FIG. 6: VGG-16 MODEL CONFUSION METRIC PLOT

FIG. 7: VGG-16 MODEL TRAIN AND TEST ACCURACY PLOT PER EACH EPOCH

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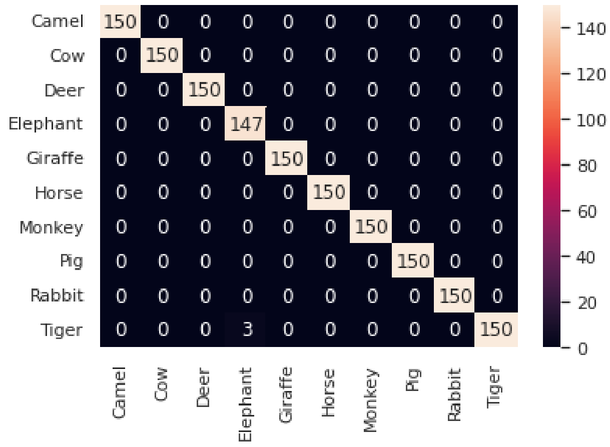

FIG. 8: VGG-19 MODEL CONFUSION METRIC PLOT

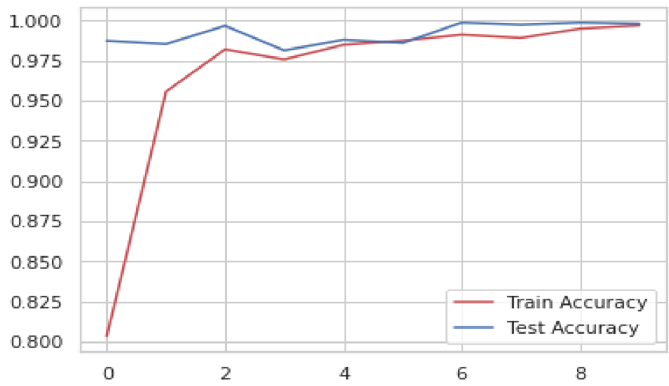

FIG. 9: VGG-19 MODEL TRAIN AND TEST ACCURACY PLOT PER EACH EPOCH

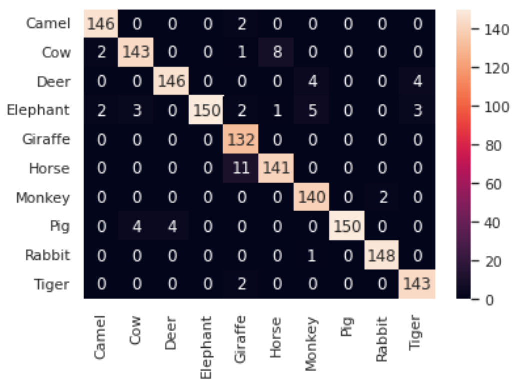

FIG. 10: MOBILENET MODEL CONFUSION MATRIX PLOT

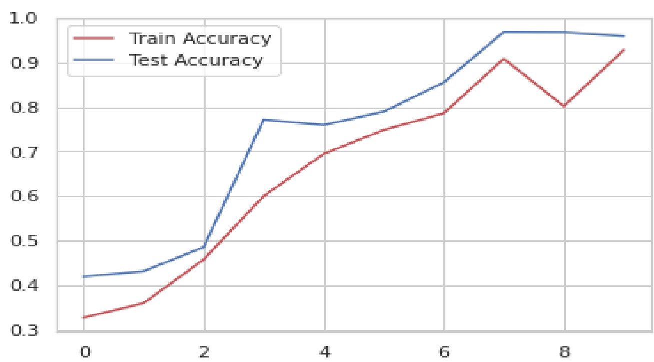

FIG. 11: MOBILENET MODEL TRAIN AND TEST ACCURACY PLOT PER EACH EPOCH

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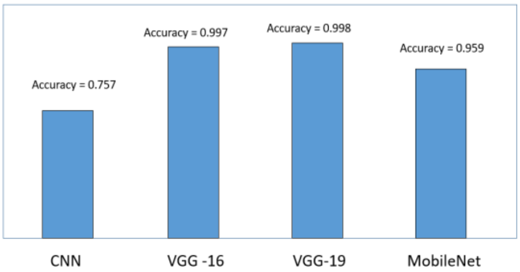

FIG. 12: ALL THE MODELS COMPARISON PLOT

Using CNN we got 75% accuracy but this accuracy is not enough we are trying to predict with 100% accuracy so we go forward with transfer learning model vgg-16. Predict 99.7% using Vgg-16 we can check in fig 6 confusion matrix and fig 7 train accuracy and test accuracy plot per each class. Then tried VGG-19, It is also similar to VGG-16 and gave 99.8 % accuracy see in fig 8 and fig 9. VGG-19 slightly better than VGG-16 small difference only there. Finally tried mobilenet model using this model we got 95.9% see the results in fig 10 and fig 11. Finally we are predicting 99.8% accuracy by using vgg-19 model. We are finalize this model as final model and save it. In deployment stage using opencv get the images from camera and apply saved model on the image predict the class. Once the model predict any animal it simple drop one mail to famer. We can see the comparison accuracy comparison between 4 models in fig 12 and VGG-19 is our final model.

V. CONCLUSION

In the present, crop vandalism by wild animals has grown to be a significant societal issue. In other words, every farmer should be conscious of the fact that animals are living things that need to be safeguarded from any potential pain while using his or her food produce. It needs immediate attention and a practical solution. Therefore, this initiative has substantial social significance since it will assist farmers in safeguarding their crops, save them from suffering significant financial losses, and spare them from making futile attempts to safeguard their farms.

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