ABSTRACT

Agriculture maintains the food requirement and also helps in supplying raw materials to many industries. Crops are mainly destroyed by wild animals. This is one of the reason for low productivity of crops. It’s not possible for farmers to staying 24 hours in farms to protect crops. Every year around 20% of crops is destroyed by wild animals. Also, irrigation of crops is one of the major problems which affects crop growth, due to irregular irrigation trends crops won’t be able to grow to its full potential. Due to irregular irrigation around 18 million hectares of crop is being destroyed every year, this is one of the major challenges. To deal with this problem a smart agriculture method and farm protection method has been proposed which deals with irrigation problem and wild animals problem.

The proposed model uses machine learning technique to detection wild animal from live video camera and gives notification to the authorized user, and smart irrigation method using IoT (Internet of Things) sensors like moisture, temperature and humidity sensor able to predict the need of water for crops. The proposed machine learning model can get the accuracy of 91% and IoT model using different Sensors able to predict the need of water for the crops.

Keywords: *Machine Learning, Agriculture, Esp8266, Moisture Prediction, Temperature Sensor, Humidity Sensor, Water Pump , Wild Animals.*

IOT BASED SMART AGRICULTURE USING LEARNING ALGORITHMS

by Ramavatar Yadav

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Student — **Project Guide**

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CHAPTER 1
INTRODUCTION

In India, Agriculture is play an important role in the country economy. Approx 65% of peoples are dependent on agriculture and approx. 41% of India's GDP is contributed by agriculture. Agriculture is backbone of India. In many parts of the country people mainly depend on rainfall and monsoon for their crop's irrigation, every year around 30% of crops wash away due to irregular water treatment to crops. Many developed counties like Germany, USA invests heavily on their agriculture to protect crops from wild animals but still they face crop loss problem, As India is a developing economy crop loss is one the major problem of the country. To deal with all of these problems surveillance plays a very important role. In many areas, including the home, hospitals, schools, and public spaces, surveillance is crucial. Surveillance can protect us from any unwanted thing that can happen to us and can play a role of evidence. The crops in the field should be protected from wild animals without harming them as they are also very integral part of our ecological diversity.

It is not possible for farmer to stay on farms all the time as any wild animal can attack and can cause loss of life and injuries. Attack of wild animals on the farms leads to poor crop engenderment, due to this problem many farmers leave their farms, and they suffer financial loss.

In the proposed method the machine learning technique is used, whenever any wild animal attacks crop the camera installed in the farm captures the video of animal the farm and gives it to machine learning algorithm this method consists of mainly two step steps preprocessing and classification step. In the first step the video is being divided into frames and each frame is being resized into a fixed, in the next step the features are being extracted from frames and given to CNN model. In the classification step the based on the threshold value the image is being classified as wild animal or not.

When any wild animal happens to present in the video the authority will gets the message that wild animal is present in the farm. In the other model IoT sensors like temperature, humidity and moisture sensor to detect soil moisture and find out the content of moisture in the soil. The data is being collected from sensors and send it to the farmer and farmer will get to know how much water is needed this will protect soil from being spoiled.

1.1 MOTIVATION

Protecting crop from wild animals and managing quantity of irrigation required for crops is one of the major challenges in today's world. The proposed approach is developed to detect animals entering farms. Here the deep learning algorithm is used, the model will predict the wild animals from live camera. After the predicting the model will predict weather the animals will comes under harmful category or not. The model CNN solve the problem of crop loss another model is developed to develop a smart irrigation system which will predict the requirement of water for irrigation the method will use IoT sensors and record the amount of water needed by crops for irrigation.

1.2 SCOPE

The proposed model can solve the long problem of crop loss problem due to wild animals and crop irrigation irregularity. The proposed model can prevent crop loss by 10 to 15 percent. By this model the use of Machine learning in farming can be done, as machine learning is a fast growing field and the scope of machine learning is not fully explored in agriculture areas.

1.3 GOAL

To develop a system which will detect animals entering the farm. Using Deep learning Algorithm, the model will predict the object for every image frame received from the Live Camera. Classify animals to harmful and non-harmful animals and take actions accordingly. To develop a smart irrigation system which predicts the water requirement for a crop using machine learning algorithm.

CHAPTER 2
LITERATURE REVIEW

Many techniques have already been put forth in the field of smart agriculture to locate wild animals and determine the amount of moisture in the soil. Smart Irrigation and Crop Protection is the title of the essay. One advantage of the model, put up by [1] is that it intends to construct and carry out the advanced communication system for smart irrigation and crop protection from invading animals. In a real-world Smart Farming testbed, the solution has been implemented and tested. According to the findings, using a SA system can cut water usage (when paired with a conventional irrigation system) by up to 71.8%.

Disadvantage: solar energy production and storage and integrate LoRa wireless Connect sensors and actuators to create a machine learning system. Another model was put up by [1]. The prototype was successfully created and put through testing such that it could detect the soil moisture readings in real-time and transmit them to the Arduino via serial communication.

Disadvantage: An application can be developed which will enable the remote monitoring of the soil moisture values and thus assisting the control of the water pump.

The key benefit of this model, according [3], is that the system was programmed to be trained utilizing the provided dataset and all sensed data from the soil moisture, temperature, and humidity sensors.

Disadvantage: Deep learning techniques can be used to improve the accuracy.

A different publication suggested a system for protecting crops from wild animals. With IoT By [4]. The model is capable of a keenly intelligent, low-cost, and energy-efficient agricultural bulwark system surveillance. The main goal is to prevent crop loss and to fortify the area against trespassers and wild animals that constitute a serious threat to agricultural areas.

Disadvantage: IR sensor can give false alert So image or video processing through CCTVs can be used to identify accurately.

Gaps in existing solution:

- Currently, farms use IR sensors and ultrasonic sensors to monitor animal activities. Any type of object can be detected by a PIR sensor or an ultrasonic device, but image recognition can be used to categorise wild animals.
- There is no remote soil moisture monitoring available to farmers. Thus, a program that allows for remote monitoring of soil moisture levels can be created, helping to facilitate the control of the water pump.

CHAPTER 3

PROPOSED WORK AND IMPLEMENTATION

3.1 Proposed Solution:

An unsupervised deep learning model for detecting wild animals in live videos is proposed. Whenever any wild animal enters the video frame, the proposed model starts working. Live video frames are being converted into frames and each frame is being given to our model. In the preprocessing phase the feature extraction is being done, in feature extraction specific features of images like shape, size, color is being extracted. After the preprocessing phase the features are sent to the classifier. In classification step CNN model is being used, CNN predicts whether the frame has wild animal or not based on a threshold value, for this model threshold value of .75 is fixed. The CNN model consists of layers like convolutional, ReLU and pooling, each layer of CNN model performs a specific task.

The other model is based on smart irrigation, The model predicts the water requirement for crops, which helps in maintaining the crop productivity. The model uses IoT based sensors like humidity, moisture, temperature etc. Which helps in predicting the need for water and records the data value over a period of time. The data value helps in maintaining crop productivity and helps in irrigation process.

3.2 Block Diagram:

A brief block diagram of the entire work done in this project is shown in Fig 3.2.1. The workflow diagram step by step is shown in fig 3.2.1.

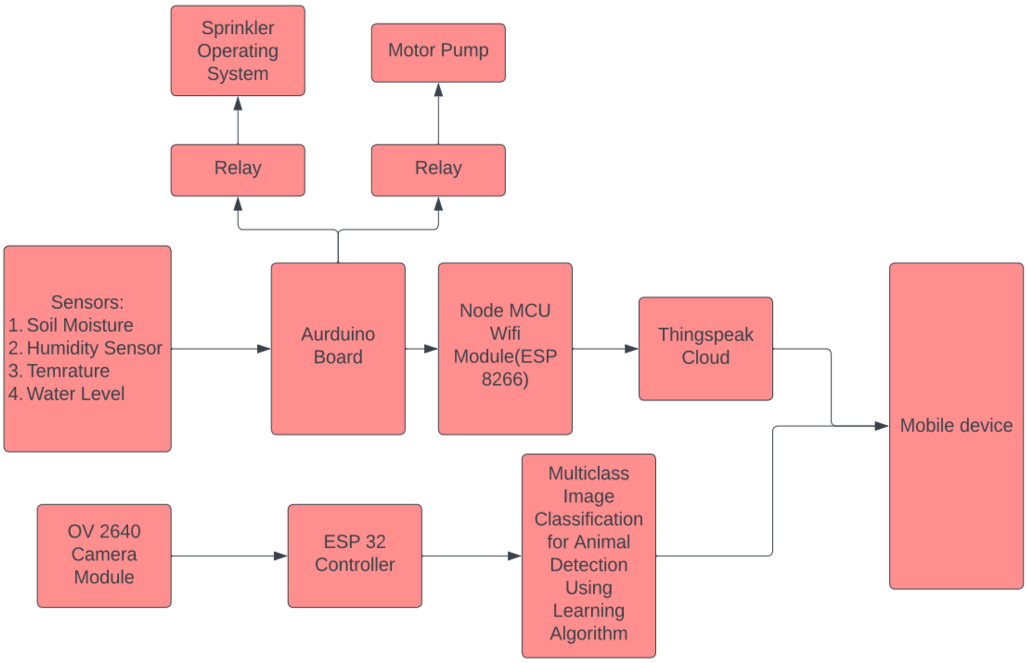

Fig 3.1: Block Diagram of proposed method

A Farming setup is installed in the farms which transfers the data collected by the sensors to the server using a microcontroller. The block diagram of smart irrigation system is represented. It consists of a microcontroller (ATmega328) which is the brain of the system. Both the moisture and temperature sensors are connected to the input pins of the controller. The two relay modules are coupled with the output pins. And water pump is connected to relay modules. The recommended crop details will be provided to the former via SMS on mobile through the wi-fi module.

The proposed system can reduce the efforts of daily watering of plants. It also conserves water for irrigation by locating the sensor at the right position above the soil level. The plants can still sustain at low moisture levels when the temperature is moderate.

The system is used to switch on/off the water pump according to the sensor readings there by automating the process of irrigation, which is one of the time-consuming activities. The system uses information from the sensors to irrigate soil which helps to prevent over irrigation (water wastage). Users can monitor the process online through a website.

3.3 METHODOLOGY:

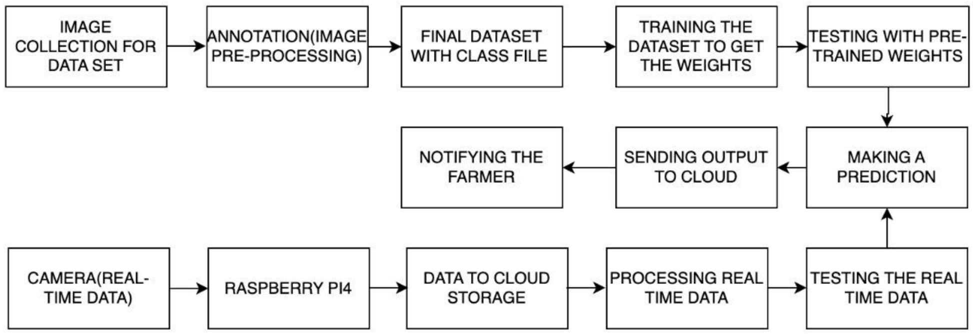

Fig 3.2: Flow Chart

3.3.1 Collecting Dataset:

The dataset consists of pictures of 10k animal images. The dataset used is being divided into training and testing. The model is trained with 80 percent of data and 20% of data for testing purposes. When the video is captured from a video camera it is divided into frames and for each frame our model test that frame has wild animal in it or not. After the data the data is being to preprocessing step.

The data collection for IoT model is done by saving sensors data at thingspeak cloud. The data from the cloud is being converted into .csv file. The .csv file is then fed into our random forest model. The model then predicts the output as content of water present in the soil.

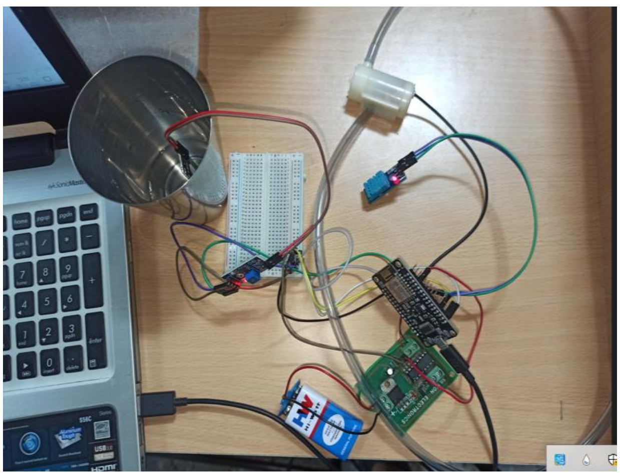

Fig 3.3: Sensor Data Collection

3.3.2 Pre-Processing:

In image preprocessing the image is resized into fixed sized images so that preprocessing can take place easily. After image resizing feature extracting takes place in feature extraction the features of images are being extracted. For example, if there is any animal in the frame the important feature of the animal is extracted like color, shape etc. It is given to a classifier to classify whether it is a wild animal or not.

The step before starting to extract and learn features is to estimate and remove the background. The background is indeed different for different scenarios as there are various methods for its removal. For instance, the background might include empty spaces or street borders. In this method, the background estimation is based on most occurrence of frequency (MOF) between video frame patches.

For the background estimation steps at first, a histogram is generated for each frame of the video which is based on pixels and their location in the image. Then the histogram of the frames in each patch is compared with each other, and the maximum values per patch are identified as background and are thus grayed. Removing the background will reduce the cost of the computing and the processing time. This step is considered as a part of the train network.

Training: In the training phase we train the model with appropriate dataset of animals. And save the training model.

Camera: From the camera we will capture the real image if any wild animal comes in the video frame the model detects that it is wild animal.

Preprocessing Realtime: The model preprocesses the frames from video. The frame is being extracted from video, and model computers the video frame by frame, whenever any wild animal comes into frame the model detects it is a wild animal or not.

Sending message to the user: Whenever the model detects wild animal, message is being send to the user that wild animal is there.

3.3.3Algorithms:

3.3.3.1 CNN Algorithm (CONVOLUTIONAL NEURAL NETWORK)

Convolutional neural network is class of deep neural network. CNN have applications in image and video recognition, image classification, medical image analysis, and natural language processing. It has five layers- Convolutional layer, Pooling layer, ReLU layer, fully connected layer, Loss layer. CNNs use relatively little pre-processing compared to other image classification algorithms.

Layer 1: Convolutional Layer

The first layer detects large features that can be recognized and interpreted easily. Convolutional layers apply a convolution operation to the input, passing the result to the next layer. A very high number of neurons would be necessary due to the very large input sizes, A (small) image of size 100 x 100 has 10000 weights for each neuron in the second layer. This problem is solved has the convolution layer reduces the number of free parameters, allowing the network to be deeper with fewer parameters.

While passing the image to the next layer each filter (neural network) is convolved across the width and height of an input image. The convolutional layer helps in training of traditional multi-layer neural networks using back propagation algorithm.

Layer 2: Pooling Layer

It partitions the input image into a set of non-overlapping rectangles and, for catch such sub-region, outputs the maximum.

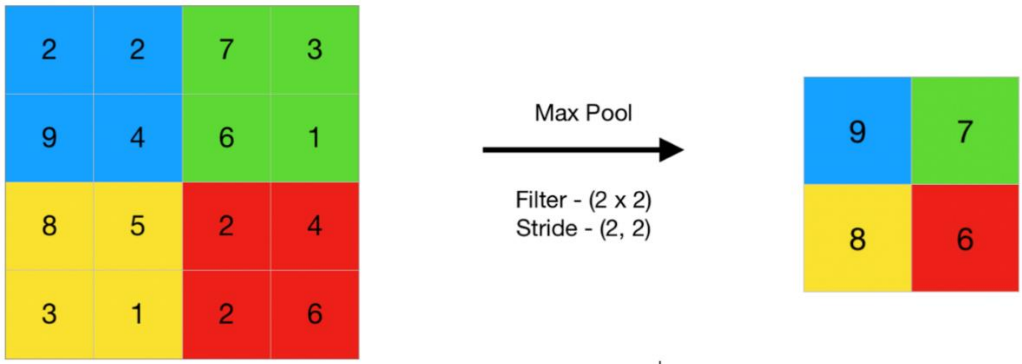

Fig 3.4: Pooling Layer Working

Layer 3: ReLu Layer (rectified linear unit)

The ReLU is an Abbreviation of rectified linear unit, which applies the non-saturation activation function { f(x)=max (0,x) }.

The max values of the pooled region are considered. Those values is given as the output values. It considers nonnegative values.

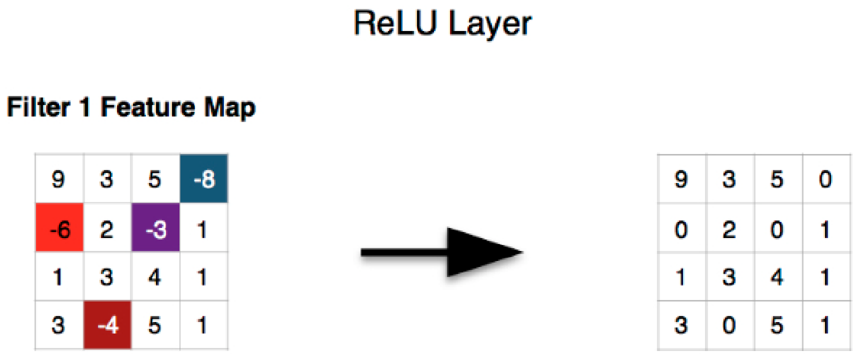

Fig 3.5: ReLU Layer Working

Layer 4: Fully Connected Layer

After several convolutional and max pooling layers, the high-level reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have connections to all activations in the previous layer, as seen in regular (non-convolutional) artificial neural networks. Their activations can thus be computed as an affine transformation, with matrix multiplication.

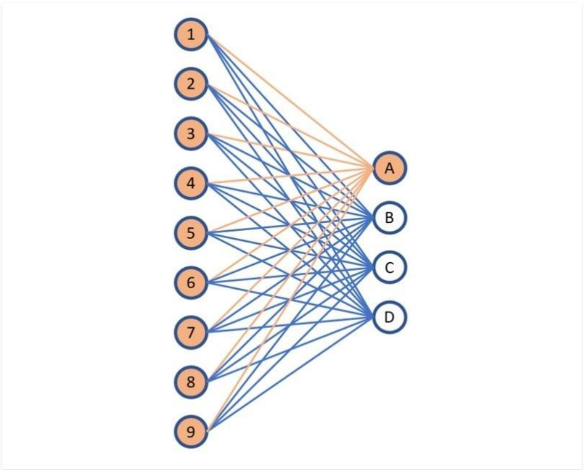

Fig 3.6: Fully Connected Layer Working

Layer 5: Loss Layer

It specifies how training penalizes the deviation between the predicted output and true labels and is normally the final layer of a neural network.

3.3.3.2 Random Forest Classifier:

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

Random Forest works in two-phase first is to create the random forest by combining N decision tree, and second is to make predictions for each tree created in the first phase.

The Working process can be explained in the below steps:

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

Step-3: Choose the number N for decision trees that you want to build.

Step-4: Repeat Step 1 & 2.

Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

3.4 VGG16 Classifier Architecture:

In the detection component, learned features which are generated in train network are given to a classifier with classes of wild animal. Features are given as individual and combined features to these networks.

VGGNet-16 consists of 16 convolutional layers and is very appealing because of its very uniform Architecture. There are a few convolution layers followed by a pooling layer that reduces the height and the width. If we look at the number of filters that we can use, around 64 filters are available that we can double to about 128 and then to 256 filters. In the last layers, we can use 512 filters.

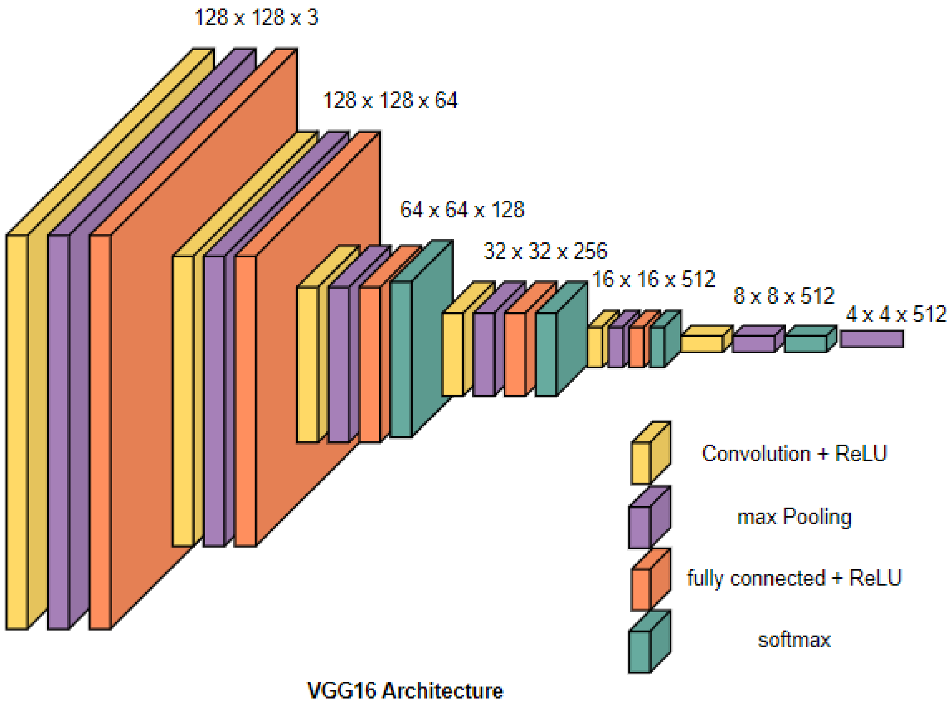

Fig 3.7: VGG16 Architecture

VGG16 Model

Layer (type)	**Output Shape**	**Param #**
input_2 (InputLayer)	(None, 128, 128, 3)	0
block1_conv1 (Conv2D)	(None, 128, 128, 64)	1792
block1_conv2 (Conv2D)	(None, 128, 128, 64)	36928
block1_pool (MaxPooling2D)	(None, 64, 64, 64)	0
block2_conv1 (Conv2D)	(None, 64, 64, 128)	73856
block2_conv1 (Conv2D)	(None, 64, 64, 128)	147584
block2_pool (MaxPooling2D)	(None, 32, 32, 128)	0
block3_conv1 (Conv2D)	(None, 32, 32, 256)	295168
block3_conv1 (Conv2D)	(None, 32, 32, 256)	590080
block3_conv1 (Conv2D)	(None, 32, 32, 256)	590080
block3_pool (MaxPooling2D)	(None, 16, 16, 256)	0
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1180160
block4_conv1 (Conv2D)	(None, 16, 16, 512)	2359808

block4_conv1 (Conv2D)	(None, 16, 16, 512)	2359808
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0
sequential_1 (Sequential)	(None, 10)	4199946
Total params: 18,914,634 Trainable params: 5,380,106 Non-trainable params: 13,534,528		

Table 3.1: VGG16 model layers

3.5 Hardware and Software requirements

Hardware components which are used in the proposed model is:

1) CPU: Intel 9th generation core i5 processor

2) RAM: 32GB, SSD: 256 GB

3) Sensors:

Sensors	Operating Condition	Singal Type
Soil Moisture Sensor	5V	Analog
DHT 11	3.3 or 5V	Analog

Table 3.2: Sensors

4)NodeMCU 8266

Software tools used:

1) Python 3

2) TensorFlow

3) Scikit learn

4) NumPy

5) Pandas

6)Colab

7)Cuda

CHAPTER 4
RESULTS

4.1 RESULTS AND ANALYSIS

The proposed model is able to perform better than traditional models for wild animal detection. The model rasnet50 which gives an accuracy of 70% compared to proposed method which gives the accuracy of 90%.The proposed model uses vgg16 model which is proven better than other traditional models.

- CNN in deep learning is being proven more accurate in classifying weather a particular has wild animal or not.

The proposed irrigation model is able to perform better than traditional models. For the proposed model an accuracy of 90% is achieved. The proposed model uses Random Forest classifier for the prediction of water requirement for the crop. The proposed model uses IoT sensors like temperature, humidity and soil moisture to collect data and send it to think speak cloud. The data from cloud is then send to our machine learning model which predicts the requirement of water for crop.

- Random forest model is being proven better than other traditional method for predicting water requirement for crops.

The snapshots for each step-in models:

4.1.1 Training the model:

Fig 4.1 shows the accuracy and loss corresponding to each epoch. The accuracy of our model is improving slowly with each epoch and also the loss is being slowly decreased.

```
63/63 [==============================] - 5s 80ms/step - loss: 0.7964 - accuracy: 0.7265 -
Epoch 4/15
63/63 [==============================] - 5s 80ms/step - loss: 0.6675 - accuracy: 0.7745 -
Epoch 5/15
63/63 [==============================] - 5s 80ms/step - loss: 0.6118 - accuracy: 0.7900 -
Epoch 6/15
63/63 [==============================] - 5s 81ms/step - loss: 0.5385 - accuracy: 0.8170 -
Epoch 7/15
63/63 [==============================] - 5s 81ms/step - loss: 0.5790 - accuracy: 0.8010 -
Epoch 8/15
63/63 [==============================] - 5s 81ms/step - loss: 0.4659 - accuracy: 0.8375 -
Epoch 9/15
63/63 [==============================] - 5s 81ms/step - loss: 0.3998 - accuracy: 0.8665 -
Epoch 10/15
63/63 [==============================] - 5s 81ms/step - loss: 0.4130 - accuracy: 0.8560 -
Epoch 11/15
63/63 [==============================] - 5s 81ms/step - loss: 0.4636 - accuracy: 0.8465 -
Epoch 12/15
63/63 [==============================] - 5s 81ms/step - loss: 0.3081 - accuracy: 0.8910 -
Epoch 13/15
63/63 [==============================] - 5s 82ms/step - loss: 0.2783 - accuracy: 0.9080 -
Epoch 14/15
63/63 [==============================] - 5s 81ms/step - loss: 0.3144 - accuracy: 0.8950 -
Epoch 15/15
63/63 [==============================] - 5s 82ms/step - loss: 0.2213 - accuracy: 0.9220 -
```

Fig 4.1: Model-1 Epochs

```
Epoch 1/10
114/114 [==============================] - 923s 8s/step - loss: 2.4673 - accuracy: 0.5937 -
Epoch 2/10
114/114 [==============================] - 90s 789ms/step - loss: 1.8383 - accuracy: 0.6294
Epoch 3/10
114/114 [==============================] - 90s 791ms/step - loss: 1.4851 - accuracy: 0.6495
Epoch 4/10
114/114 [==============================] - 89s 778ms/step - loss: 0.9326 - accuracy: 0.6879
Epoch 5/10
114/114 [==============================] - 89s 784ms/step - loss: 0.8774 - accuracy: 0.7027
Epoch 6/10
114/114 [==============================] - 88s 773ms/step - loss: 0.8684 - accuracy: 0.7091
Epoch 7/10
114/114 [==============================] - 90s 792ms/step - loss: 2.7491 - accuracy: 0.6324
Epoch 8/10
114/114 [==============================] - 89s 780ms/step - loss: 1.0965 - accuracy: 0.6420
Epoch 9/10
114/114 [==============================] - 90s 790ms/step - loss: 0.9866 - accuracy: 0.6684
Epoch 10/10
114/114 [==============================] - 90s 786ms/step - loss: 0.9762 - accuracy: 0.6852
```

Fig 4.2: Model-2 Epochs

Fig 4.2 shows the model is trained with 10 iterations, training loss is not constant after every iteration, and training accuracy is being increased after ever iteration as seen in figure 4.2.

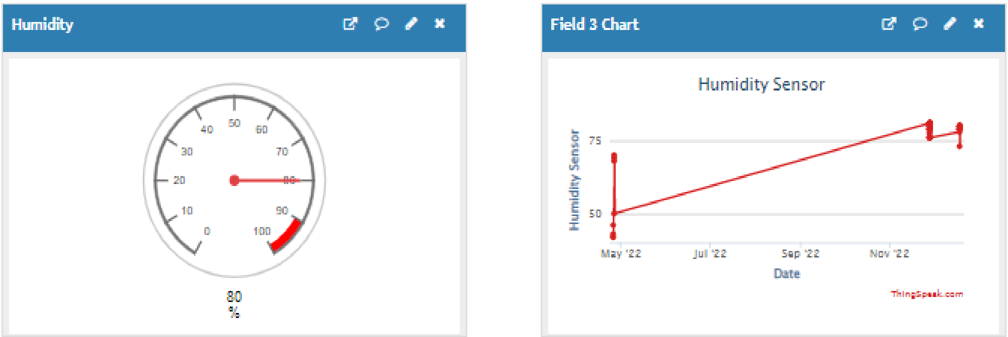

Fig 4.3: Humidity Graph

Fig 4.3 indicates the data collected from humidity sensor and then stored on thingspeak cloud. The content of water in air which is 80% at a particular time, and the graph indicates the timeline of humidity over a period of time.

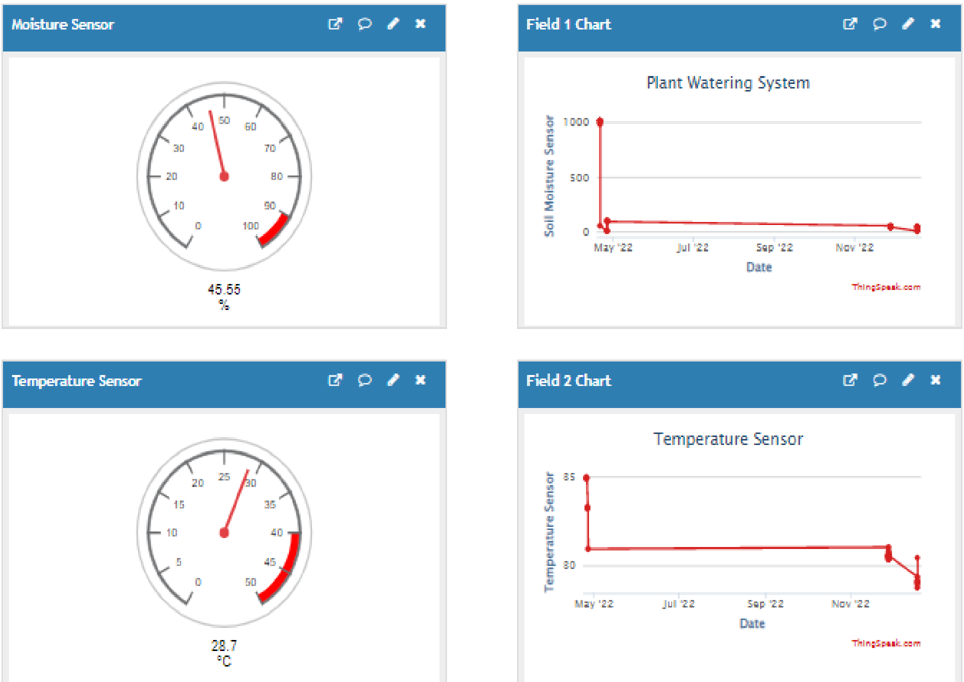

Fig 4.4: Moisture and Temperature Graph

Fig 4.4 indicates the data collected from moisture sensor and temperature sensor and then stored on thingspeak cloud. fig. The content of water in the soil which is 45.5% at a particular time, and the graph indicates the timeline of moisture of soil and temperature over a period of time.

4.1.2 Loss graphs:

Fig 4.5 shows the training as well as testing loss values for model-1 decreases after every iteration. It can be observed that training loss is gradually decreased.

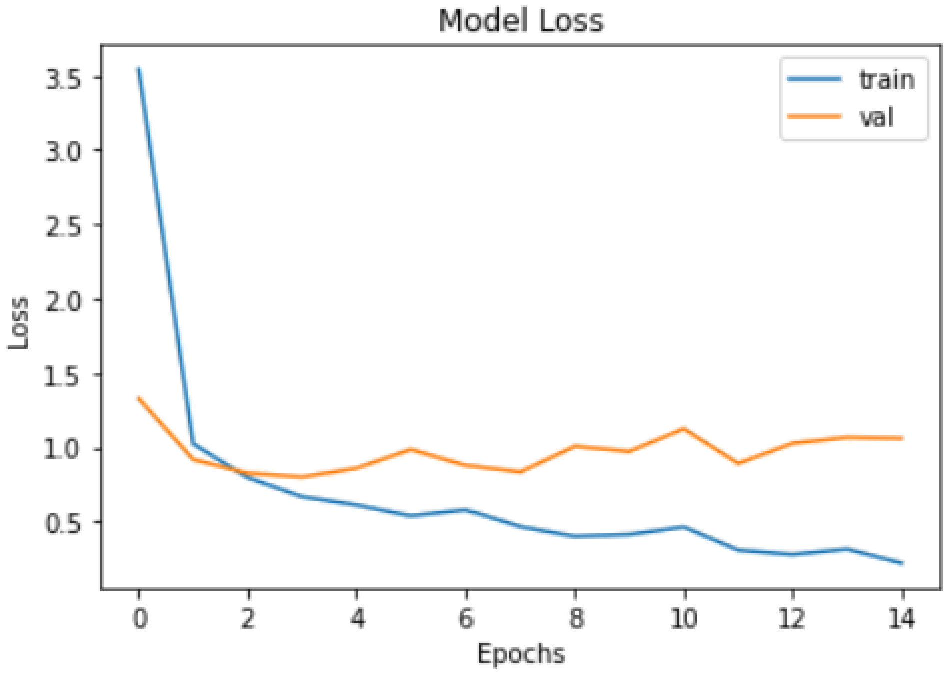

Fig 4.5: Epoch vs loss graph for Model -1

Fig 4.6 shows the training as well as testing loss values for model 2. It can be observed that training loss is constant over the period and testing loss decreases instantly and then becomes constant over a period.

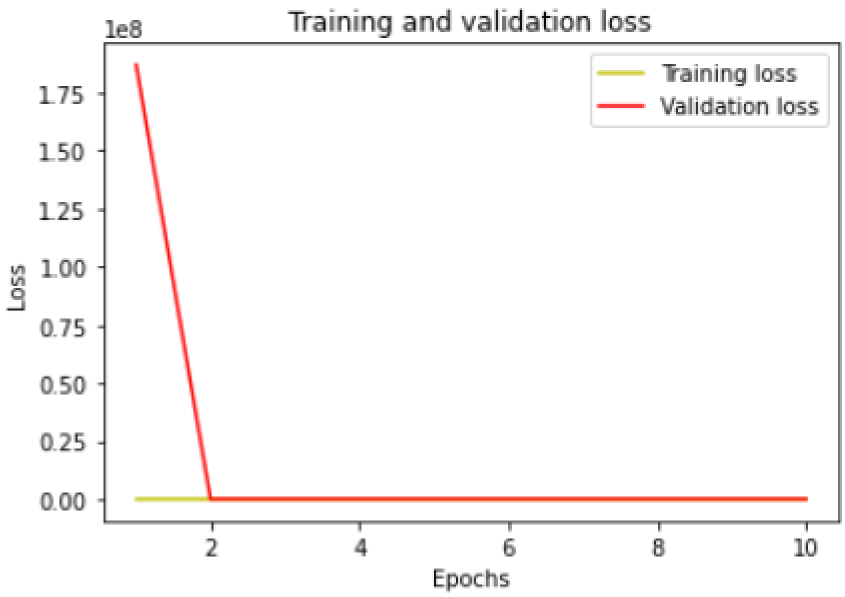

Fig 4.6: Epoch vs loss graph for Model-2

4.1.3 Accuracy Graphs:

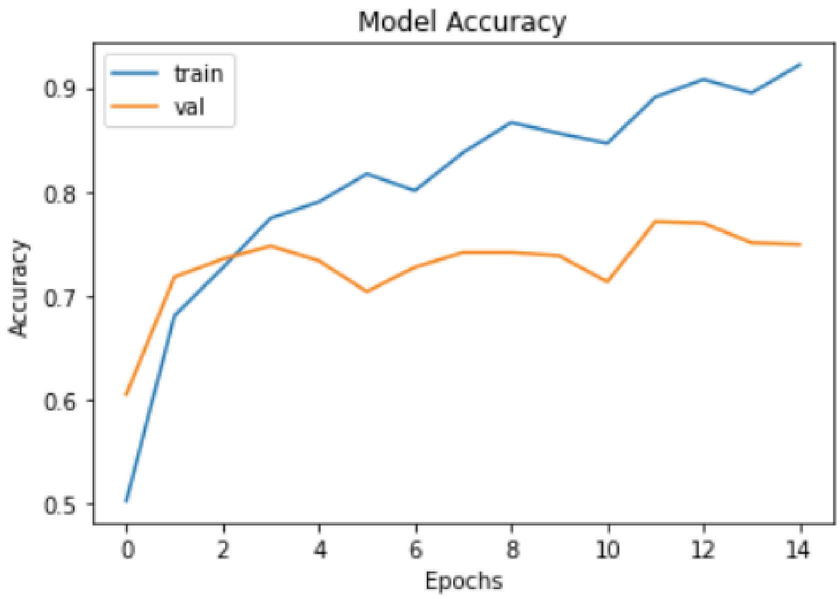

Fig 4.7: Epoch vs Model Accuracy graph for Model-1

Fig 4.7 indicates the proposed model in fig gives training accuracy of 90% and validation accuracy of 74% as seen from above graph. The model outperforms other model consideration the amount of computation required for testing and training of data.

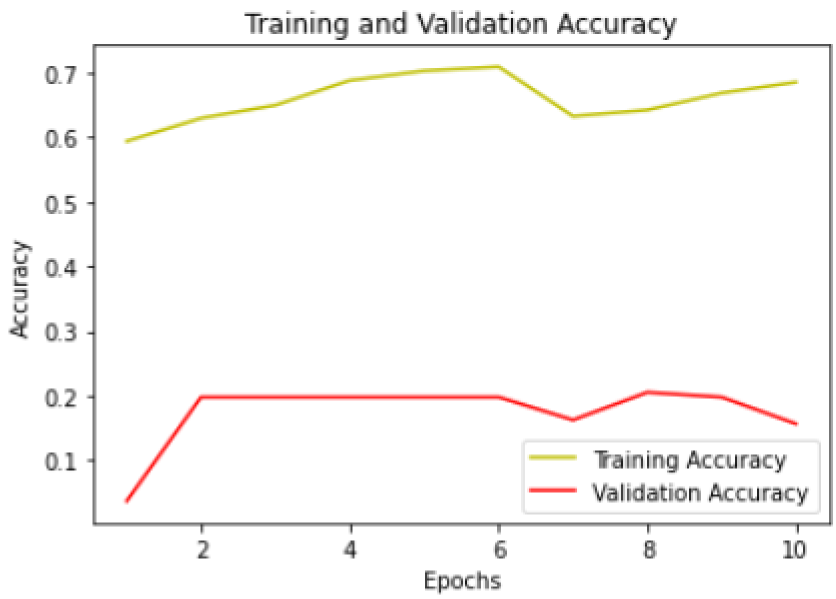

Fig 4.8: Epoch vs Model Accuracy graph for Model-2

Fig 4.8 indicates the proposed model in fig gives training accuracy of 72% and validation accuracy of 15% as seen from above graph. The model is insufficient in comparison to other models.

The test accuracy, Loss and Validation Accuracy for each model are below:

Results: The Training Accuracy, Loss and Validation Accuracy of Model-1 and 2 are showed in table 4.1.

	Training Accuracy	**Loss**	**Validation Accuracy**
Model 1(VGG16)	0.9220	0.2213	0.7492
Model 2(ResNet50)	0.6852	0.9762	0.1566

Table 4.1 Model 1 and Model 2 Comparison

In Table 4.1 indicates the proposed VGG16 model has training accuracy of 74% and testing accuracy of 92% and loss of 22% which is good in comparison to traditional resnet50 model.

Fig 4.9: Animal Detection in a particular frame

Fig 4.9 indicates that the wild animal is arrived in the particular frame and it is detected by our model and it is denoted by a rectangular frame.

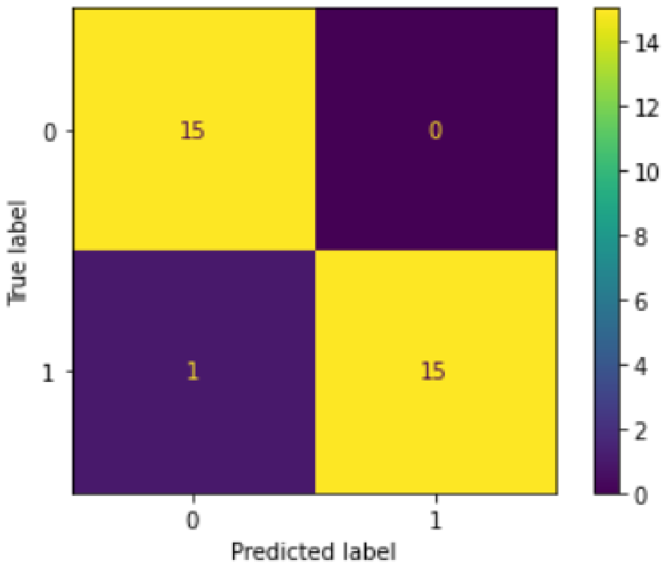

Fig 4.10: Confusion Matrix

Fig 4.10 indicates the true and predicted label on testing data set,15 true positive and 15 true negative, 0 false positive and 1 false negative. The model gives precison of 1, recall of 0.93,accuracy of .97 and F1 score of .9

4.1.4 Comparison graphs

The comparison graphs for CNN Model – VGG16, ResNet50.

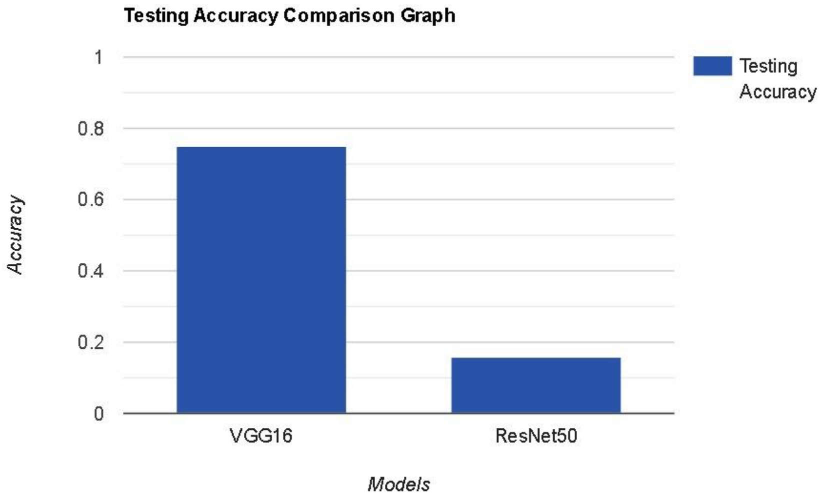

Fig.4.11: Testing Accuracy Comparison

Fig 4.11 indicates The proposed vgg16 model gives better testing accuracy as it consists of 16 convolution layer, as compared to restnet50 which has an accuracy of 15%.

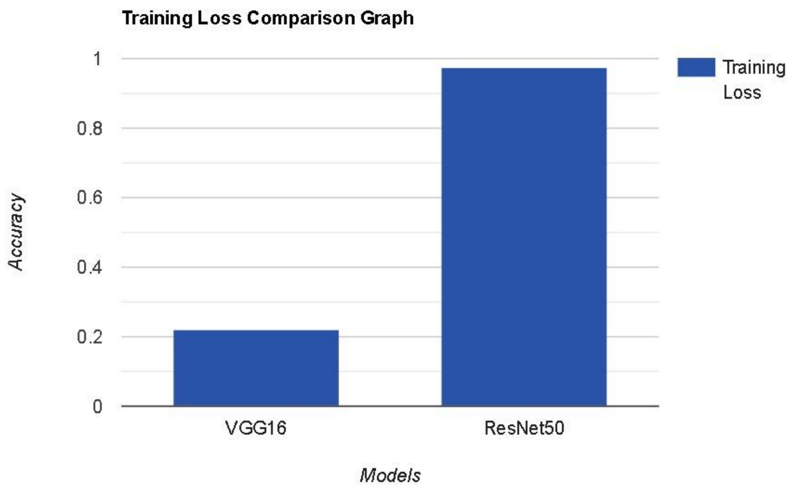

Fig.4.12: Training Loss Comparison

Fig 4.12 indicates The proposed vgg16 model has less training loss compared to traditional ResNet 50 which has training loss of 97% means less the loss and more accuracy.

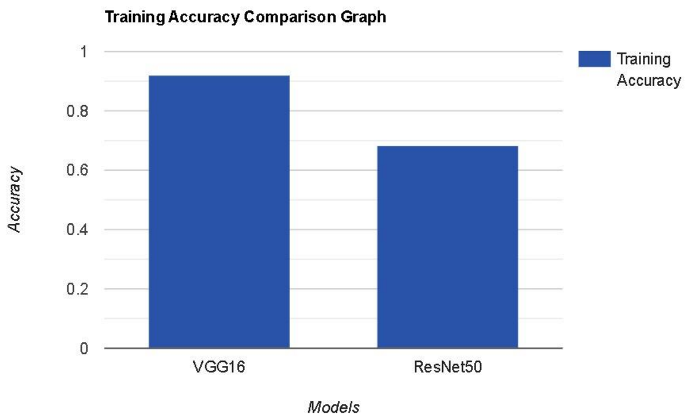

Fig.4.13: Training Accuracy Comparison

Fig 4.13 indicates the proposed vgg16 model has better training accuracy which is 92% compared to resnet50 which is 68%. The proposed vgg16 consists of 16 convolutional layers which gives better result compared to traditional model.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 CONCLUSION:

The quandary of farm crop by animals has become one of the major issues in current time the proposed model deal with this problem in better and accurate way compared to other traditional model, the proposed model has achieved an accuracy of 74% which is better in many scenarios compared to traditional approach. The other proposed IoT based irrigation system has proven better and accurate compared to traditional model, the model uses data collected on cloud to predict the content of water in soil and how much water needed for better irrigation, the overall accuracy of 97 percentage is being achieved by random forest classifier model. The proposed model can solve the problem of crop devastation and can do smart irrigation better.

5.2 FUTURE WORK

The proposed model can be further extended by adding more sensors and actuators. Further the model can be optimized by adding more CNN layers and training with larger datasets to gain more accuracy and make predictions more accurate. Furthermore an app can also be developed which gives better user experience and can enhance our model to much more larger userbase.

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