AI Based Smart Agriculture – Leaf Disease Prediction Using Optimized CNN Model

Ashwini A Nadig[1] and Dr. Geetishree Mishra[2]

[1]*M. Tech Scholar, Dept of ECE, BMSCE, Bengaluru, Karnataka, India*
[2]*Assisstant professor, Dept. of ECE, BMSCE, Bengaluru, Karnataka, India*

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Abstract -*Internet of Things (IoT) is an answering technology to several problems of the agriculture it not only helps to get the sensory readings of the physical parameters but also helps to interconnect those information over the internet using specific protocols. This paper discuss regarding the use of IOT in agriculture for smart farming and also focuses on some of Image processing techniques for leaf disease detection . The sensors integrated helps in detecting the moisture of the soil, pH of the soil, temperature in atmosphere and also humidity in atmosphere. Images of the plant leaves are collected from the field and then Preprocessing based on Gaussian filter is carried out on the image, after segmentation disease identification is done using the fast R-CNN, faster R-CNN and Mask R-CNN methods, then the best method for identification is chosen among the three methods by comparing the results from the three models.*

Key Words: smart agriculture, Deep learning, fast R-CNN, faster R-CNN and Mask R-CNN.

1. INTRODUCTION

Agriculture plays an important role in the economy of every country. Crop produced by farmers must be in a proper condition to achieve expected profit. Advancements in technology must be used in this domain to save and make products market ready. But due to continuous change in weather and lack of technology access in this field, farmers are facing a huge challenge to protect their produce from different diseases that are unexpected and occurred at any time. In smart agriculture, a variety of data from various sources are combined. Sensors for agriculture and farming can measure a number of different parameters For instance, a multitude of environmental factors might affect crop health. To understand variations within and between fields, the establishment of a financially viable, environmentally responsible farming system is aided by smart agriculture. The Internet of Things (IoT) is fundamentally what powers the Agriculture Cyber-Physical System (A-CPS) (IoT). Due to its acceptance and advantages, IoT has even entered the agricultural industry. The majority of current research in "smart agriculture" focuses on increasing food production. Soil moisture sensor, temperature sensor, humidity sensor and pH sensor are connected to raspberry pi through Arduino nano to collect the sensory data from the field and then they are further used for crop recommendation.

Traditional way of disease detection is based on observation and time consuming which requires experts to be present on the field. Sometimes misdiagnosis of many diseases may cause harm to crops, products and consumers who are consuming the product. Artificial Intelligence (AI) plays a significant role in every vertical like agriculture. AI can be useful to solve most common issues in agriculture. It can be used to identify various leaf diseases in an early stage. Using automatic plant leaf disease detection methods farmers will get help to reduce their losses and to improve the productivity. We have used Deep Learning technique which is a subset of AI to detect the leaf disease in an early stage. Nowadays, Convolutional Neural Networks are considered as the leading method for object detection. In this paper, we considered detectors namely Fast Region-Based Convolutional Neural Network (Fast R-CNN), Faster Region-Based Convolutional Network (Faster R-CNN) and Mask Region-Based Convolutional Network (Mask R-CNN). Each of the architecture should be able to be merged with any feature extractor depending on the application or need. We consider some of the commercial/cash crops, cereal crops, and vegetable crops and fruit plants such as tomato, bell pepper, tomato etc... images of these leaves are selected for our purpose.

With the aid of machine learning algorithms, we are able to make precise decisions and analyze data collected from sensors, processed on the server, and assessed. The data detected by the sensor from crop yield for various characteristics such as humidity, temperature, precipitation, pH quality, and so on is stored by IoT systems and then used to forecast plant types that have a direct impact on crop development, after that a prediction choice is made to forward to the end user for further action that will help the end user. This system will also define a cropped image of a plant using image processing and feature extraction algorithms. For photos gathered as a dataset, an optimized CNN model is created and used. The goal of optimization is to increase the system's prediction accuracy and the classification of true positive samples. Raspberry Pi receives the sensor data gathered by Arduino nano, and k-mean algorithm is then applied to the data for crop recommendation.

2. RELATED WORKS

Here, we take some of the papers related to smart agriculture and Plant leaf diseases detection using various advanced techniques some of them are shown below,

In paper[1], The author of this research suggests a solar-enabled smart agriculture system with crop disease prediction to help farmers make their work easier and more profitable. The solar sensor node is made up of a designed soil moisture sensor, a DHT11 sensor, and an embedded camera module. The soil moisture levels assist in automating the irrigation water pump, and crop-related camera pictures are transferred to the ThingSpeak cloud for storage and subsequent processing.

In paper[2], the author of this paper has taken into account all of agriculture's issues and highlighted the importance of numerous technologies, particularly IoT. Wireless sensors, UAVs, cloud computing, and communication technologies are all thoroughly covered for this purpose. A fuller understanding of recent research initiatives is also given.

In paper[3], An Internet of Things (IoT)-based control system for improving farming in rural areas is presented by the author. The control system's various parts and improvements are reviewed and examined from all angles, including testbed evaluation. Better energy, latency, and throughput performance has been obtained with the IoT MAC and routing solution.

In paper[4], the authors present a faster region-based CNN-based method (Faster Regional-CNN) for detection of smaller objects. Using the concept of two-stage detection, the author proposes a new and improved loss function for regression of bounding boxes in the positioning stage and uses bilinear interpolation to enhance the RoI pooling operation to address the issue of positioning deviation, In the recognition step, the author uses improved nonmaximum suppression method to prevent loss of overlapping objects and multi-scale convolution features fusion to increase the information in the feature map.

In paper[5], the authors suggested that When used for the purpose of rust quantification, the Mask Regional-CNN outperformed conventional image processing methods. The extensive set of parameters that must be tuned presents one of the difficulties in employing Mask R-CNN; the author's study looks tuning of the parameters automatically. For the first time, hyper-parameter tuning and genetic algorithm on the Mask Regional-CNN at this scale are used in this study (GA).

3. METHODOLOGY

a. Block diagram of setup

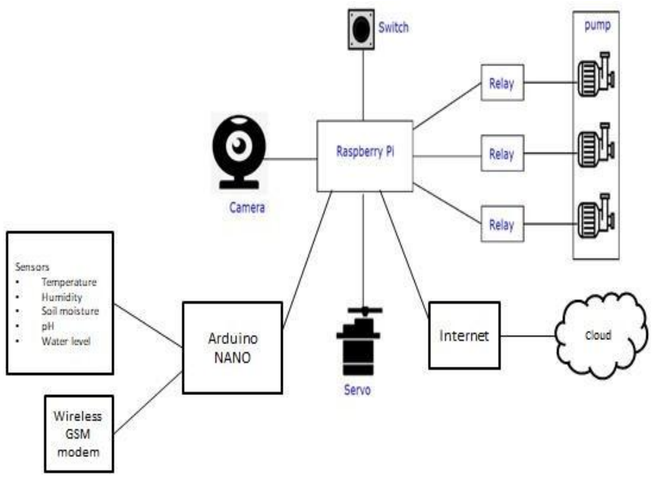

Fig -1: block diagram of the complete process

The block diagram consists of a web camera, raspberry pi, press switch, soil moisture, and temperature and humidity sensors. The camera module captures the image of the leaf; the captured image is given as an input to the raspberry pi module for further image processing and then compared with the images present in the database using the optimized CNN algorithm. The results from the image processing are sent to the mobile phone via internet. And further after the successful detection of disease the plants have to be provided with suitable pesticides to avoid any further spread of disease so based on the disease detected suitable pesticide will be intelligently chosen by the system and sprayed to the plant using Relay and water pumps.

Based on the sensory data sensed by sensors irrigation control is also done, that is certain threshold will be set for all the physical parameters and if the sensed data is below that threshold or above that threshold then the water will be supplied to the agriculture land based on the current environmental requirements.

The optimized CNN algorithm among the 3 algorithms is choosen finally and the output result from the model along with the suitable pesticide to be sprayed is sent as message to the farmer using Fast2SMS api. The crop recommendation is done by considering the sensory data that are sensed in the farm and based on those values a suitable crop that can be grown is recommended the data flow diagram for that is given in next sub-section.

b. Crop Prediction data flow diagram

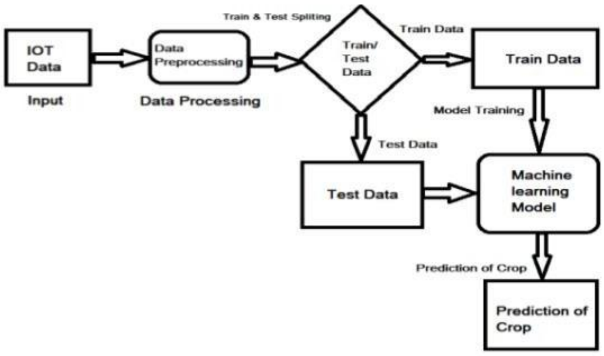

Fig -2: Crop Prediction data flow diagram

The methodology of machine learning is used to forecast crop yields in order to maximize crop profitability. Figure 2 demonstrates the stream of estimation of the expected crop yield As shown in the previous flow diagram, sensors are installed on the farm to detect data related to humidity, temperature, precipitation, and pH. K-mean algorithm is used to characterize sensed data.

c. Image Processing

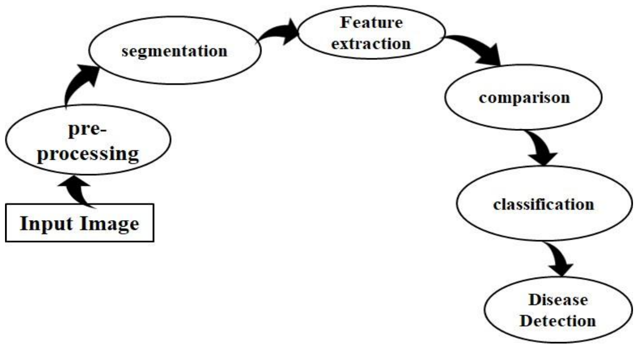

Fig -3: Image processing data flow diagram

- Input: The Leaf image dataset are implemented as input. The input images are taken in the format .jpg or .png.
- Preprocessing: The collected images are subjected to preprocessing. In the Preprocessing step image resize and noise removal is performed.
- Segmentation: In the Segmentation process, the following CNN are implemented.
    - Fast R-CNN Algorithm
    - Faster R-CNN Algorithm
    - Mask R-CNN Algorithm
- It is based on ROI Algorithm using Bounding Box.
- Classification: In this step to implement the SVM classifier is used, to identify diseased or not.
- Performance Estimation: In this step, we can analyses some performance metrics.

d. Fast vs Faster vs Mask R-CNN

Fast R-CNN:

The approach is similar to the R-CNN algorithm. But, instead of feeding the region proposals to the CNN, we feed the input image to the CNN to generate a convolutional feature map. From the convolutional feature map, we identify the region of proposals and warp them into squares and by using a RoI pooling layer we reshape them into a fixed size so that it can be fed into a fully connected layer. From the RoI feature vector, we use a softmax layer to predict the class of the proposed region and also the offset values for the bounding box.

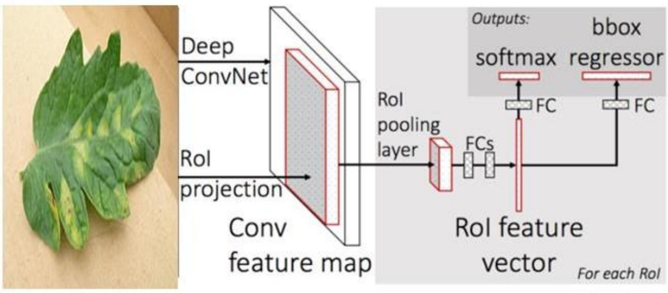

Fig -4: Layer diagram of Fast R-CNN

Faster R-CNN:

It is similar to Fast R-CNN, the image is provided as an input to a convolutional network which provides a convolutional feature map. Instead of using selective search algorithm on the feature map to identify the region proposals, a separate network is used to predict the region proposals. The predicted region proposals are then reshaped using a RoI pooling layer which is then used to classify the image within the proposed region and predict the offset values for the bounding boxes.

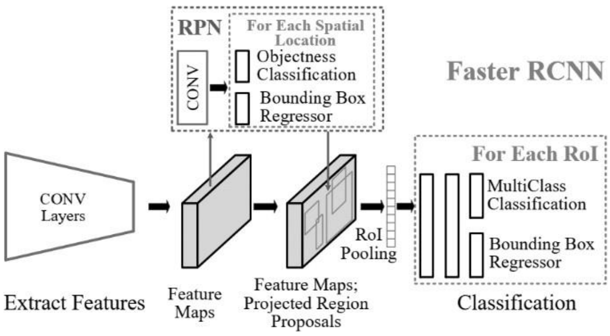

Fig -5: Layer diagram of Faster R-CNN

Region Proposal network:

Region proposal is an area where objects can possibly be found. It uses CNN to find regions of interest using binary classifiers. CNN layers of Regressor plot bounding box around possible objects and later by finding Intersection over Union we can decide which boxes possibly contain regions of interest. Region of Interest (ROI) can be calculated by dividing area of intersection by area of union.Once regions of interest get finalized, the next step is to have ROI Pooling. This step gets input from CNN as a feature map and Region of interests from regressor. ROI pooling is used to extract fixed size windows from feature maps that is helpful to extract labels as a final output. It will produce fixed size feature map from different size regions using max pooling.

MASK R-CNN:

Mask R-CNN was built using Faster R-CNN. While Faster R-CNN has 2 outputs for each candidate object, a class label and a bounding-box offset, Mask R-CNN is the addition of a third branch that outputs the object mask. The additional mask output is distinct from the class and box outputs, requiring the extraction of a much finer spatial layout of an object. Mask R-CNN is an extension of Faster R-CNN and works by adding a branch for predicting an object mask (Region of Interest) in parallel with the existing branch for bounding box recognition. Mask R- CNN adopts the same two-stage procedure with an identical first stage (which is RPN). In the second stage, in parallel to predicting the class and box offset, Mask R-CNN also outputs a binary mask for each RoI.

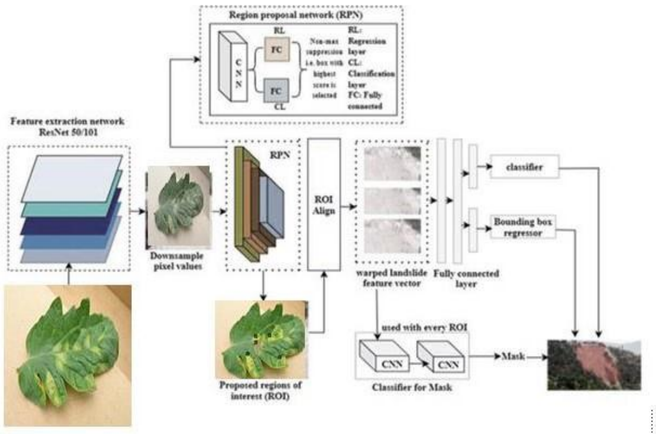

Fig -6: Layer diagram of Mask R-CNN

4. EXPERIMENTAL RESULT

DATASET: The PlantDoc dataset is used, PlantDoc is a dataset of 2,569 images across 13 plant species and 30 classes (diseased and healthy) for image classification and object detection. There are 8,851 labels. leaf dataset was divided into two parts that is training and testing for predicting type of disease. The 80% of the data was passed to all these three R-CNN model for training with batch size 32 and epochs 50.

Fast R-CNN

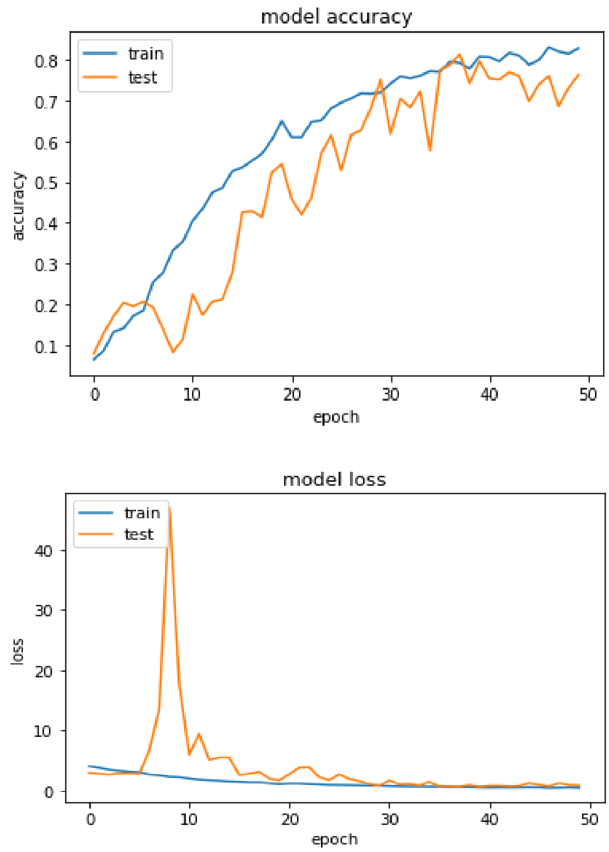

Fig -7: Model accuracy and loss graph for Fast R-CNN

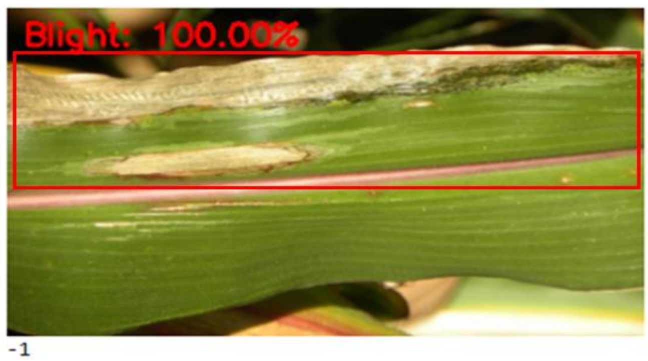

Fig -8: Output of the fast-RCNN Algorithm

The performance analysis of Fast R-CNN is provided in the below figure

```
------Accuracy------
('FASTCNN Accuracy:', 77.51937984496125, '%')
------Classification Report------
              precision    recall  f1-score   support

           0       0.88      0.79      0.83       274
           1       0.59      0.73      0.66       113

    accuracy                           0.78       387
   macro avg       0.74      0.76      0.74       387
weighted avg       0.80      0.78      0.78       387


Confusion_matrix
[[217  30]
```

Fig -9: Performance report of Fast R-CNN

Faster R-CNN

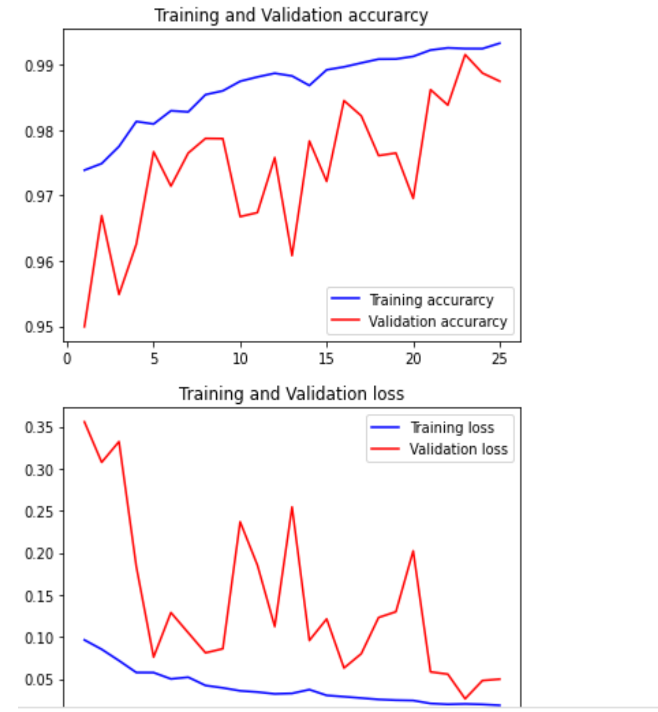

Fig -10: model accuracy and loss graph of faster R-CNN

Fig -11: Output of the faster-RCNN Algorithm

The performance analysis of Faster R-CNN is provided in the below figure

```
------Accuracy------
('FASTRCNN Accuracy:', 82.17054263565892, '%')


------Classification Report------
              precision    recall  f1-score   support

           0       0.89      0.84      0.86       264
           1       0.69      0.79      0.74       123

    accuracy                           0.82       387
   macro avg       0.79      0.81      0.80       387
weighted avg       0.83      0.82      0.82       387
```

Fig -12: Performance report of Faster R-CNN

Mask R-CNN

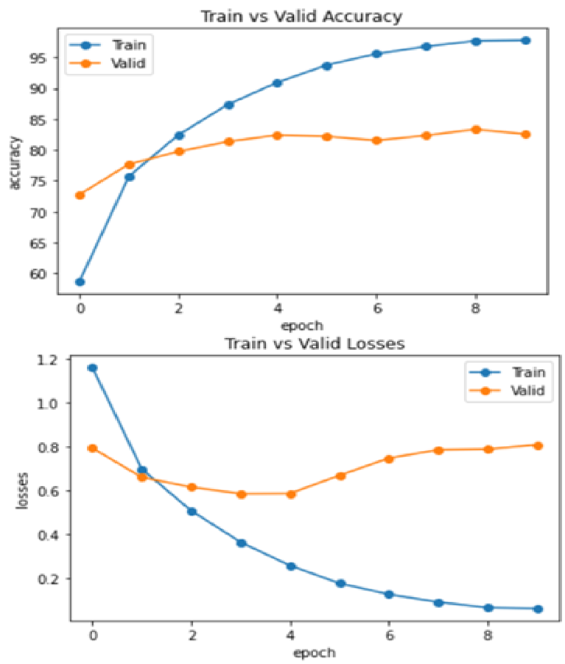

Fig -13: model accuracy and loss graph of Mask R-CNN

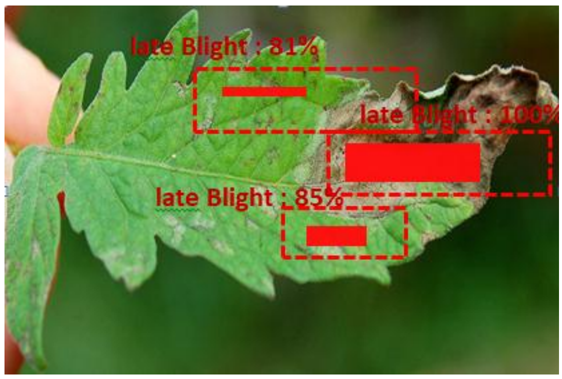

Fig -14: Result of Mask R-CNN

The performance analysis of Mask R-CNN is provided in the below figure.

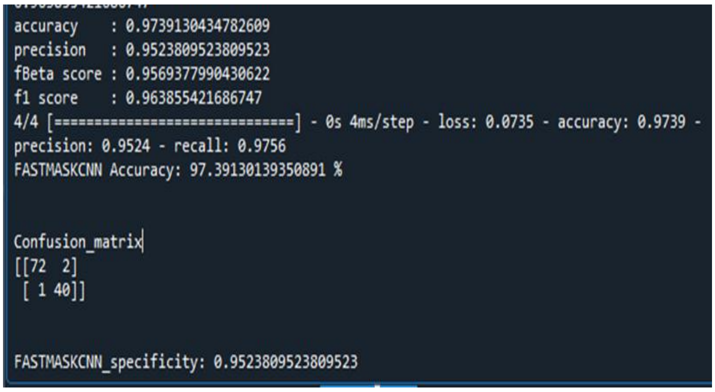

Fig -15: Performance report of Mask R-CNN

HARDWARE PART:

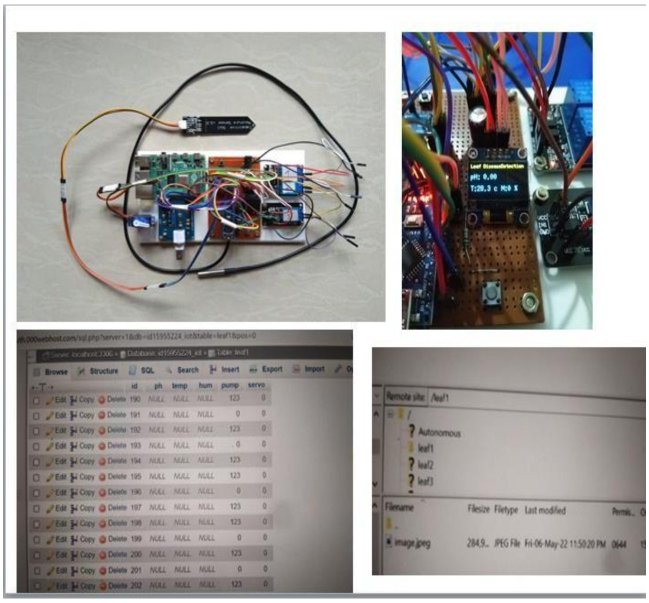

Fig -16: figure of system and sensor readings

Crop Recommendation Output

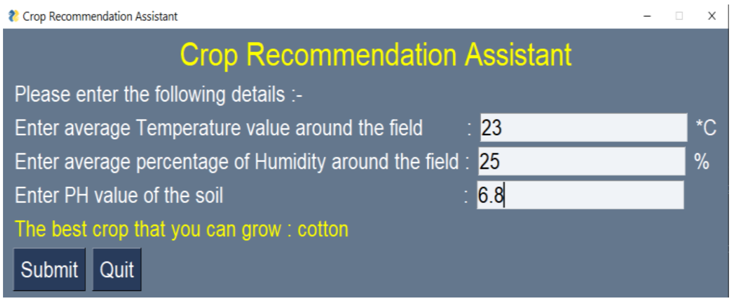

Fig -17: Performance report of Mask R-CNN

Pesticide Recommendation Output

Fig -18: figure of system and sensor readings

RESULT COMPARISON

Method	Accuracy	Precision	f1score
Fast R-CNN	**90.32**	**88**	**83**
Faster R-CNN	**93.65**	**89**	**86**
Mask R-CNN	**96.5**	**95**	**95**

5. CONCLUSIONS

In this paper, a optimized CNN among the Fast R-CNN, Faster R-CNN and Mask R-CNN for plant disease detection is selected. According to the provided performance analysis result we can say that Mask R-CNN is having a highest accuracy of 97.39%. so we can say that mask R-CNN is suitable for plant disease detection among the three models. The sensory data collected from the agriculture land is fed to the crop recommendation model and suitable crop that can be grown in the agriculture land is suggested by the k-mean algorithm model. The pesticide that has to be sprayed is also suggested based on the disease detected.

6. REFERENCES

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