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

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Abstract - *The Internet of Things is a technology that provides solutions to a number of issues in agriculture. It not only assists in obtaining sensory readings of physical properties but also in connecting those data over the internet utilizing particular protocols. This research focuses on several image processing approaches for leaf disease identification as well as the usage of IOT in farmland for smart farming. The built-in sensors aid in determining the soil's moisture content, pH level, air temperature, and humidity level. Plant leaf image is Gathered from the field have undergone rigorous preprocessing, which are then subjected to preprocessing based on a Gaussian filter, segmentation, and disease identification using fast R-CNN, faster R-CNN, and Mask R-CNN methods. From the comparative analysis it is identified that mask R-CNN is most suitable method for accurately predicting the plant disease.*

Key Words: Smart agriculture, Machine learning, Deep learning, IoT, Fast R-CNN, Faster R-CNN and Mask R-CNN.

1. INTRODUCTION

Every nation's economy is significantly influenced by agriculture. To generate the anticipated profit, farmer's crops must be in good condition. To save money and prepare products for the market, technological advancements must be applied in this field. Farmers, however, are finding it extremely difficult to safeguard their crop from various illnesses that might strike at any time owing to unpredictable weather patterns and a lack of technological access in this industry. A wide range of environmental factors may have an impact on crop health, as measured by sensors used in agriculture and farming. The development of a financially successful, ecologically friendly agricultural system is supported by smart agriculture, which seeks to identify variances within and across fields. Cyber-Physical System based on agriculture is basically powered by the Internet of Things (IoT) (IoT). IoT has even made its way into the agriculture sector as a result of its acceptability and benefits. The majority of "smart agriculture" research being done now is geared at boosting food output. To gather sensor data in the field and use it for crop suggestion, soil moisture sensors, temperature sensors, humidity sensors, and pH sensors are linked to raspberry pi using Arduino nano.

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 work, 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.

Making accurate judgments and analyzing sensor data that has been processed on the server and evaluated is made possible with the help of machine learning algorithms. IoT systems save sensor data from crops for various features like atmosphere temperature, pH level, atmosphere humidity, and so forth. These data are used to forecast plant species that directly affect crop development. Following this, a prediction decision is taken to forward the prediction to the end user for some additional action which will help the end user. An improved CNN model is developed and applied for the photographs collected as a dataset. The aim of optimization is really to improve the categorization of real positive samples and prediction accuracy of the system. Two systems are configured one to receive the data and one two process, and the data is then processed using the k-mean technique to suggest crops.

RELATED WORKS

Here, we have taken some of the papers related to smart agriculture and Plant leaf diseases detection using various advanced techniques.

Venkanna Udutalapally et al. [1] recommended a smart agricultural system with plant disease prediction that is solar-enabled to assist farmers to make their work easier and more profitable. Real-time demonstrations of the suggested method's deployment are provided. The solar sensor node is made up of a designed soil moisture sensor, a DHT11 (temperature and humidity) sensor, and an embedded camera. When compared to the current solutions, the suggested approach is more energy-efficient since it uses solar power to run the solar sensor node. The soil moisture levels assist in automating the irrigation water pump, and crop-related camera pictures are transferred to the ThingSpeak which is a cloud platform for storage and subsequent processing.

Numerous methods have been suggested by various authors for the purpose of smart agriculture and plant disease detection, Brief discussion on some of the papers related to this work is discussed below.

Muhammad et al. [2] the authors of this paper have taken into account all of agriculture's issues and highlighted the importance of numerous technologies, particularly IoT. Wireless sensors, unmanned aerial vehicles, and cloud computing, and communication technologies are all thoroughly covered for this purpose. A fuller understanding of recent research initiatives is also given. Additionally, a number of systems which are dependent on Internet of things and their architectures are offered with regard to farming applications. To help researchers and engineers, a list of the present issues the sector is facing is provided, along with predictions for the future. All of this leads to the conclusion that every square foot of farmland is essential to maximising crop yield. However, using IoT-based sensors that are sustainable and communication technology is not an option—it is required if we are to deal with every inch in the right way.

Wen-Liang Chen et al. [3] created the RiceTalk application, which uses IoT devices independent of image to identify rice blast disease, depending upon the AgriTalk IoT platform for agriculture. According to the author's suggested method, AI may be automatically trained to learn and interpret agriculture sensors that produce non-image data in real time. The AI model is handled as just an IoT device by RiceTalk, making it possible to manage it similarly to other IoT devices. This strategy successfully combines AI with the IoT platform. According to the study, the average measure of temperature and the relative humidity's min/max and range measurements all significantly affect the forecast of rice blasts. The average humidity metric might be misleading, especially when the humidity variance (min/max) is considerable. In comparison to other weather indicators, barometric pressure plus rainfall have little substantial effect on net prediction results. The humidity measurements already account for the effects of rainfall, thus they might not even add much extra information for prediction.

N. Ahmed et al. [4] proposed a crop health monitoring system based on the combination of cutting-edge technologies such as the Internet of Things, machine learning, and uav based remote sensing. Heterogeneous data is created by combining this sensory information that differs in both nature (i.e., observed parameter) and temporal fidelity. Multiple sources, including IoT sensors as well as a drone which has a multispectral camera placed on it, were used to gather the multimodal data. The length and frequency of the generation of this multi-source data varied. Following that, this data was integrated and tagged to carry out supervised classification at a common temporal resolution. Each pixel was classified as healthy, unhealthy, or stressed using machine learning techniques including SVM and NB as well as many deep learning models.

S Kumar et al. [5] presented The study described gCrop, an system based on IoT for measuring leaf growth that makes use of machine learning along with computer vision. The system uses a low-powered training model that can be used in environments with limited resources. The technique first determines the size of the leaves before estimating their age. The final results demonstrate that the suggested method can determine the dimension with an accuracy of 98-99% based on various leaf stages. Furthermore, the preliminary findings of age prediction demonstrate a good match with real plant growth. However, due to a lack of sufficient datasets, the results do not capture the growth stage of longer time periods.

Liu Liu et al. [6] presented wild pest monitoring using deep learning model. The author of this research has proposed a novel deep learning technique merging hybrid local and global activation features for autonomous insect tracking in industrial equipment to concurrently perform 3 key tasks—localization then classification and finally severity estimation. With the help of the global activated feature pyramid GaFPN structure, this method effectively realised efficient and automatic feature extraction. The author also suggested employing activation which is local to enhance the position-sensitive properties of pest boxes for strong locations. When combined with an enhanced pest data set obtained by our designed stationary pest monitoring equipment, this system beat state-of-the-art methods in tasks including pest localization, classification, and severity prediction.

2. METHODOLOGY

In this section the entire implementation methodology has been discussed.

a. Block diagram of setup

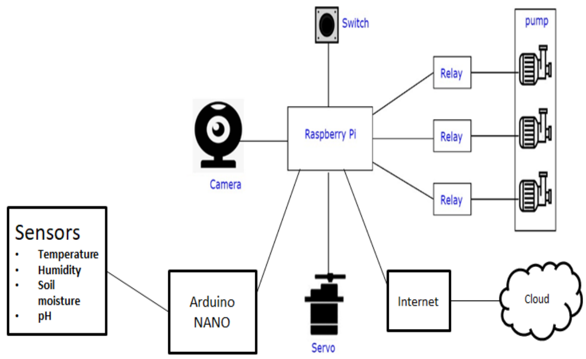

Fig -1: block diagram of the complete process

A web camera, a Raspberry Pi-4, a push switch, a soil moisture sensor, and DHT11 (temperature and humidity) sensors are included in the block diagram. The camera module takes a picture of the leaf, which is then fed to the raspberry pi board for additional image processing and comparison with pictures already in the database using the appropriate CNN technique. 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.

The temperature and soil moisture sensor sensed through the sensors and based on the sensed data irrigation control is done as the amount of water required by the farmland is based on the surrounding environment and soil condition so based on the sensed data‘s servo motor controls the irrigation that is amount of water to be supplied to the land.

The optimized CNN algorithm among the 3 algorithms is chosen 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

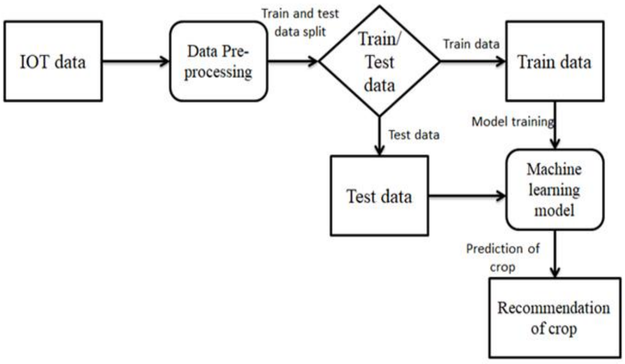

Fig -2: Crop Prediction data flow diagram

To maximize crop profitability, crop yield forecasts are made using machine learning technology. The flow of estimation for the anticipated crop output is shown in Figure 5. On the farm, sensors are installed to collect information about humidity, temperature, soil moisture, and pH, as demonstrated in the previous example. Sensing data is characterized using the K-mean technique. The forecasted outcome displays the condition of the soils as well as which soils may be best for various crops. Temperature and humidity sensors, such as the DHT11, are chosen for real-time monitoring of temperature and humidity. This sensor has been shown to be more accurate and precise. It uses a thermistor and a capacitive humidity sensor to monitor the humidity in the air, and it delivers a digital signal to an Arduino Uno port pin on the data pin. The DHT11 has a temperature range of -40 to 80 °C and a humidity range of 0 to 100% RH.

c. Image Processing

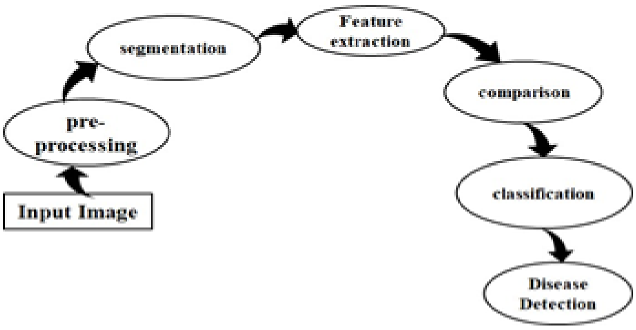

Fig -3: Image processing data flow diagram

- 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 SVM classifier is implemented, to identify whether the plant is diseased or not.
- Performance Estimation: In this step, Performance analysis for the models is given.

d. Comparison of Fast, Faster and Mask R-CNN

Fast R-CNN:

Fast R-CNN was created to address the issues with R-CNN and boost performance. Although it does not use the original image, Fast R-CNN still uses selective search to derive region recommendations. In order to generate a convolutional feature map, the input image is fed into the CNN. The convolutional feature map is then used to choose regional suggestions. The convolutional feature map is then used to choose regional suggestions. The regions of interest (RoIs) are then reshaped by the RoI pooling layer before being mapped to a feature vector by fully linked layers. Both bounding box offset and softmax prediction is produced by each vector (Roi).

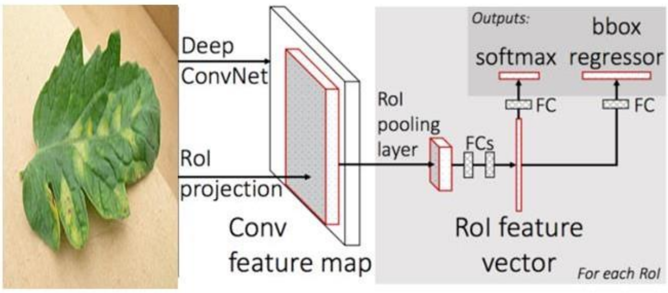

Fig -4: Architectural diagram of Fast R-CNN

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.

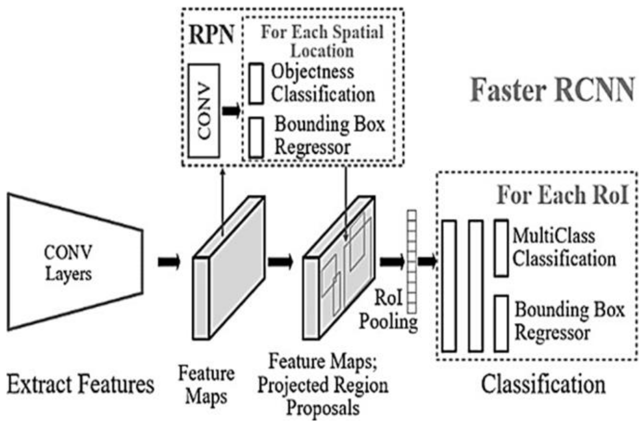

Fig -5: Architectural diagram of Faster R-CNN

Region Proposal network:

The Selective Search algorithm is used by the Regional-CNN and Fast Regional-CNN models to generate the region proposals. Each proposal is fed to a CNN that has already received training. The RPN offers few benefits:

1. A network which can be trained as well as adapted to the task of detection is now employed to generate region proposals.

2. The proposals can be trained end-to-end to be optimized for the detection job because they are created using a network. As a result, it gives excellent region proposals when compared to more generic approaches like Selective Search and EdgeBoxes.

3. The image is processed by the RPN utilising the same convolutional layers as the Fast R- CNN detection network. In contrast to algorithms like Selective Search, the RPN produces proposals in a similar amount of time.

4. The Fast R-CNN and the RPN can be combined or unified into a single network because they both use the same convolutional layers. Training is thus only performed once.

The RPN works on the last convolutional layer's output feature map, which is shared with the Fast R-CNN.

MASK R-CNN:

A codebase with high performance for object identification algorithms, for instance Mask R-CNN, was developed by Facebook AI Research (FAIR) as part of Object detection. Faster R-CNN is altered by including an additional branch for predicting object mask in addition to the present branch for bounding box identification. The mask branch uses a Fully Convolutional Network (FCN) applied on each Regional of Interest to forecast a segmentation mask at the pixel level (RoI). According to authors, the new branch only incurs a minimal computational penalty of 20% on a typical model while still operating at a frame rate of 5 for the top 100 detection boxes. Overall, the Mask R-CNN is modest to set up and train, with a flexible design that facilitates efficient experimentation. The Mask R-CNN process has two steps, similar to the Faster R-CNN. The input is scanned in the initial stage to identify potential object-containing regions. The proposed regions are classifier, bounding boxes, and masks are simultaneously constructed in the second stage.

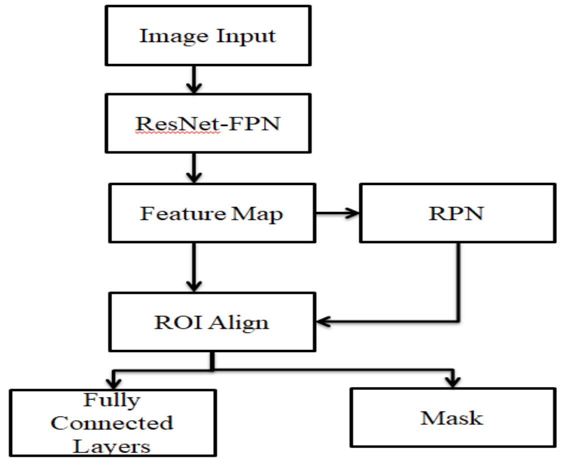

Fig -6: Process flow of Mask R-CNN

3. EXPERIMENTAL RESULT AND ANALYSIS

In this work PlantDoc dataset has been 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.

3.1. PARAMETERS VALUE FOR ALL THREE MODELS:

Parameters	Values	Description
Epochs	50 (Fast R-CNN) 25(Faster R-CNN) 10(Mask R-CNN)	Specifies how many times the entire training set is iterated through the network.
Batch Size	32	Refers to the quantity of training data utilised for each epoch even before network's weights are modified.

Learning rate	1e-3	This parameter determines how substantially the weights must change in response to the detected mistake.
Optimizer	Adam optimizer	The cost/loss function is reduced using optimization functions in machine learning, and by reducing the cost/loss function, we may attain the goal of having little variation between the anticipated and actual output. One such optimization method that is employed in place of the conventional stochastic gradient descent is Adam.

3.2. Training Accuracy and Loss Graph.

For the CNN models that are implemented, the training vs. validation accuracy along with training vs. validation loss is plotted. The relationship between training and validation accuracy shows that the model will be generalized and is consistently improving as training accuracy increases and validation accuracy decreases.

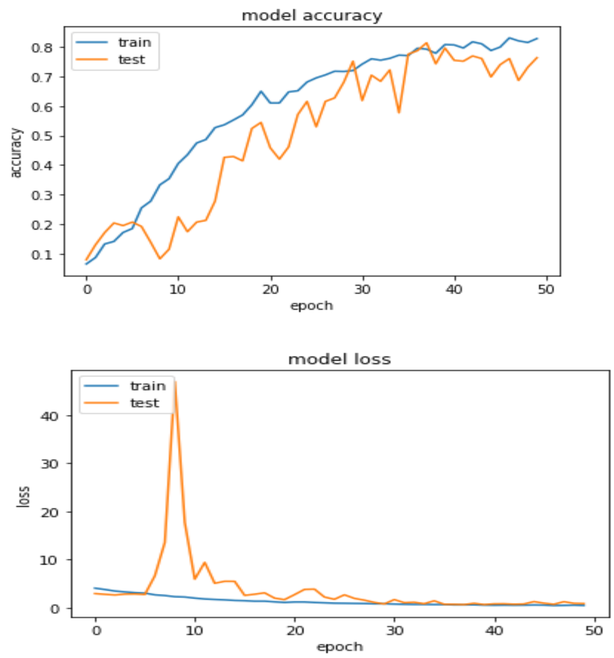

Fig -7: Model accuracy and loss graph for Fast R-CNN

Fig-7 shows the accuracy vs epoch and loss vs epoch graph for Fast R-CNN. Epoch number used for fast R-CNN is 50 it was observed that loss function is guaranteed to be computed over all data items within an epoch in order to provide the quantitative loss estimate at the specified epoch and draw a curve across each epoch. Only a portion of the total dataset receives the loss after each cycle.

Fig -8: Model accuracy and loss graph for Faster R-CNN

Fig-8 shows the accuracy vs epoch and loss vs epoch graph for Faster R-CNN. Number of epochs taken into consideration for this model is 25. Peak accuracy was observed in the range of 15-20 we can say that maximum accuracy is achieved during this range of epoch number.

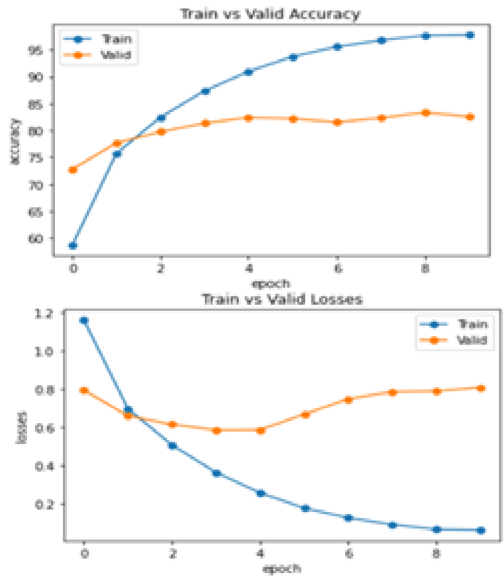

Fig -9: model accuracy and loss graph of Mask R-CNN

Fig-8 shows the accuracy vs epoch and loss vs epoch graph for Mask R-CNN. Number of epochs taken into consideration for this model is 10. We observed that model has a good learning rate as seen from the loss vs epoch curve. And there is no overfitting as observed from the accuracy vs epoch curve.

3.3. TESTING IMAGES ON THE THREE MODELS:

Plant disease detection result from all the three CNN models is shown in the below given figures.

Fig -10: Output of the fast-RCNN Algorithm

Fig-10 shows the output from the testing after the training of the Fast R-CNN model. It was observed that when a corn leaf image affected by blight is provided as a input to the model the model accurately classifies the plant disease class.

Fig -11: Output of the faster-RCNN Algorithm

Fig-11 shows the output from the testing after the training of the Faster R-CNN model. It was observed that when a tomato leaf image affected by early blight is provided as a input to the model the model accurately classifies the plant disease class as early blight.

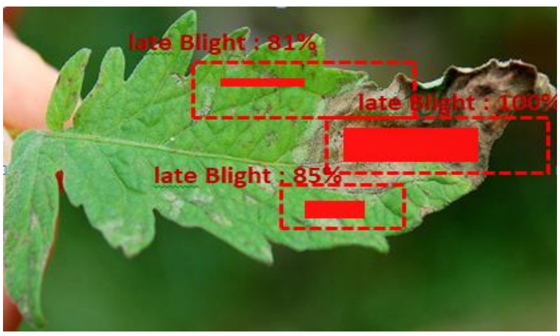

Fig -12: Result of Mask R-CNN

Fig-12 shows the output from the testing after the training of the Mask R-CNN model. It was observed that when a tomato leaf image affected by late blight is provided as an input to the model the model accurately classifies the plant disease class as early blight. We can also observe the mask output along with the bounding box output.

3.4. PERFORMANCE PARAMETERS FOR ALL THE THREE MODELS:

Accuracy and Precision along with Recall, and F1-Score of the Fast Regional-CNN Faster Regional- CNN and Mask Regional-CNN models are discussed below.

The result is referred as the True Positive outcome that is TP if the model accurately predicts the picture of a plant as harbouring the illness. The result is referred as the True Negative outcome that is TN if the model accurately predicts that the plant will not have the illness.

The result is referred as the False Positive outcome that is FP if the model wrongly forecasts the picture of a plant as carrying the illness. The result is referred as the False Negative outcome that is FN if the model incorrectly forecasts the picture of a plant as not harbouring the illness.

The performance analysis of Fast R-CNN, Faster R-CNN and Mask 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 -13: Performance report of Fast R-CNN

```
------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 -14: Performance report of Faster R-CNN

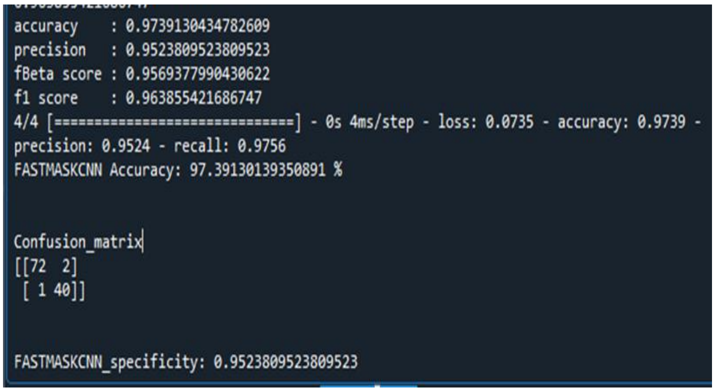

Fig -15: Performance report of Mask R-CNN

3.5. HARDWARE IMPLEMENTATION:

In the below given figure the complete hardware setup is depicted. The sensors are attached to the raspberry pi board and the led display connected to the pi board displays the sensor readings. Picture taken using the web camera is sent to the cloud along with the readings from sensors and then irrigation control, disease identification, pesticide spraying and crop recommendation is done.

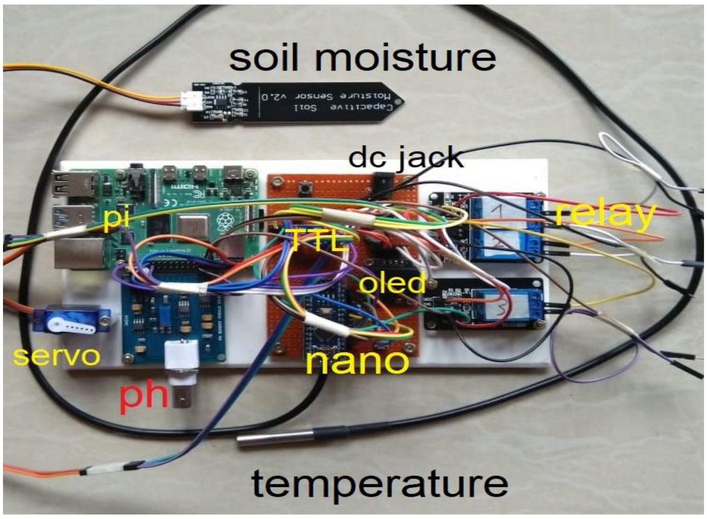

Fig -16: Hardware Implementation

3.6. RESULT OF Crop Recommendation and Pesticide Recommendation:

The data from sensors is given as an input to the crop recommendation model which is built using the k-mean classification algorithm. The dataset used is an excel sheet which has data as all the sensor thresholds and crop that can be grown in such threshold.

Based on the disease detected a suitable pesticide which can be sprayed is also recommended which is also shown in the below figure. The disease detected and pesticide to be sprayed is sent as a message to farmer's mobile using Fast2SMS apk.

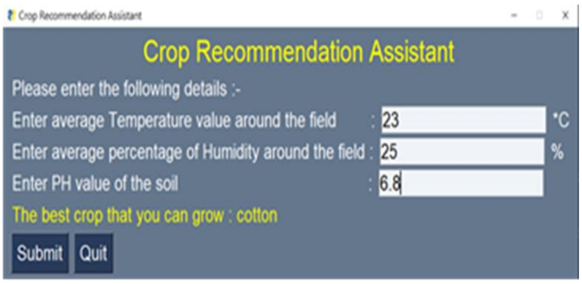

Fig -17: Crop Recommendation Output

Fig-17 shows the output of crop recommendation. When temperature, Humidity and Ph value is fed to the model it uses k-mean algorithm for classification and finally provides the suitable crop that can be grown as output.

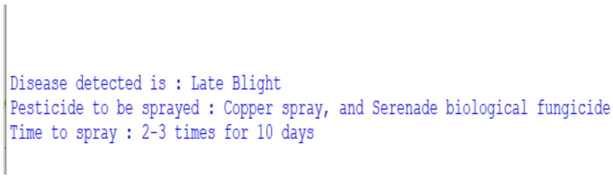

Fig -18: Pesticide Recommendation Output

Fig-18 shows the Pesticide Recommendation output. Once the disease is detected suitable pesticide that can be used and how much times the pesticide has to be sprayed is recommended.

RESULT COMPARISON:

It was observed that Mask R-CNN is achieving high accuracy when compared to other two R-CNN algorithms and it is also having high precision and Recall when compared to other 2 models.

Table -1: Result comparison Table

Method	Accuracy	Precision	Recall	f1score
Fast R-CNN	**90.32**	**88**	**79**	**83**
Faster R-CNN	**93.65**	**89**	**86**	**86**
Mask R-CNN	**96.5**	**95**	**97**	**95**

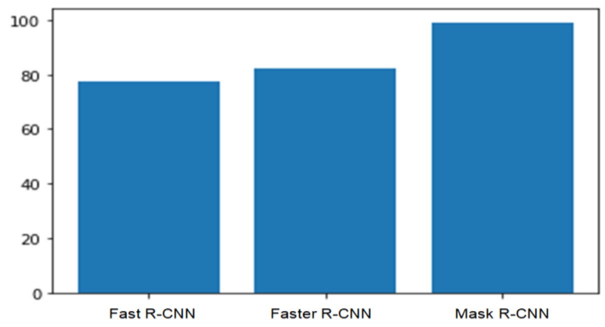

Fig -18: Accuracy Comparison of 3 models

Table-1 shows the result comparison of all the three models it is clearly evident that out of the three models Mask R-CNN is performing efficiently with an accuracy of 96.5%.

4. CONCLUSIONS

An optimized CNN among the Fast Regional-CNN, Faster Regional-CNN and Mask Regional-CNN for plant disease detection is selected. According to the result performance analysis it is observed that Mask R-CNN is having a highest accuracy of 97.39%, It is evident 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 farm land is suggested by the k-Means algorithm model. The pesticide that has to be sprayed is then suggested based on the disease detected.

Future Work:

In Hardware:

An app can be developed as further step of this work. More sensors can be used such as soil nutrient sensor and rainfall sensor to increase accuracy of crop recommendation.

In Software:

YOLOv5 can be used as a new model and to replace the faster R-CNN model with YOLOv5 to improvise the run time.

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