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Deep Learning-Based Rice Leaf Diseases Detection Using Yolov5

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Abstract:

The rice crop in the Agriculture field is playing an important role in the economy of Pakistan and fulfilling the needs of the living hood of human beings. The rice leaf faces several diseases like Bacterial Bligh, Brown Spot, Blast, and Tungro. This research attempts to create a simple and best model for rice leaf disease detection using the deep learning model Yolov5. The model has been upgraded to v5 which is the latest version of Yolo. The performance and accuracy of object detection using Yolov5 are better than Yolov3 and Yolov4 models. The envisioned recognition system has numerous applications but here focused on the agriculture field to increase crop productivity by detecting plant diseases at an early stage. This model can differentiate and successfully detect rice leaf diseases. The rice leaf images dataset is downloaded from the Kaggle website, the dataset contains 400 images of leaves infected by a disease. This paper uses the Google collab platform to train, validate and test the model for rice Leaf disease detection. All necessary steps to be implemented, the rice leaf disease are detected and fully described. The developed model utilizes epochs: 100. The experimental results show that the deep learning model created with 100 epochs has shown the best performance with precision, recall, and mAP values of 1.00, 0.94, and 0.62, respectively.

Keywords: *Roboflow; Rice leaf Disease; deep learning; Yolov5.*

1. Introduction

An Agriculture sector plays a central role in the economy of Pakistan as it contributes 19.1% to GDP and absorbs 42.3% of the labour force [1]. It plays an important role in foreign exchange earnings and assists to develop the other sectors of government. The government also promotes and introduces new technologies for modern and smart agriculture system it is the second-largest sector and remain the largest employer. Nearly 62% of the country's population resides in rural areas and is linked directly or indirectly with agriculture for their livelihood. The Agriculture sector has strong linkages with the rest of the country's economy. The economies are not fully captured in the statistics while on the one hand, the sector is a primary supplier of raw materials to the downstream industry, contributing substantially to Pakistan’s exports on the other. It is a large market for industrial products such as fertilizer, pesticides, and tractors [2-4].

Deep learning plays an important role in various applications of the smart Agriculture system [5-8]. Because Deep Learning provides a suitable solution for the smart Agriculture sector including the basic communication to cloud computing that can be accessed directly and remotely or locally gets a message on the

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cell phone through the wireless sensor network like user interface and deep learning provides the agriculture operations automation such as inventions make the agriculture industry high growth in crops [9-13]. Agriculture is the most efficient sector of our economic growth.

1.1 Rice Leaf Diseases

Many diseases attacked the rice plant from birth to fruit. The following are the most dangerous rice plant diseases which are discussed in this paper.

1.2 Bacterial Blight

The bacterial blight is a very harm full disease that effected rice leaves and plants as shown in figure 1. It destructs the life of the rice plant the loss of the grain of the crop maybe 70% and it affected a lot of areas of the field more than a hundred acres [14]. It is attacked during the initial days of plant growth. It happens when strong winds are running or heavy rain occurs this disease spread the bacteria surrounding the field when bacteria blight effect on rice plant the rice plant leaf become yellowing colour the infected leaf become roll up which means the disease progresses the leave change yellow to straw colour. When bacterial blight spread the field it gives poor-quality grain. This disease may be controlled in the most efficient, cheapest, and most reliable way to control.

Fig. 1. Bacterial Blight

The nitrogen required in balance amount and provide the water to filed remove weeds and keep the field clean this disease is controlled in another way usage of biological control like antagonists of pathogens it is effected way to remove the bacterial blight from crops.

1.3 Blast

The rice blast disease reason is a fungus. It is the most important disease in the world The rice Blast is a cereal disease field that lost 10 to 30% of grain [15]. When this disease attacked small necrotic appear on the leaf initially. Which will become larger the rice plant disease symptoms occur on the leaf blade and leaf sheath. Infection later affected the rice's incomplete grain filling. This disease affected the root of plants and fungus can infect the plant growth stage. The rice blast is a more dangerous disease it destroys the whole crop of the field. Symptoms can be the spot. The crop shape and size change may be dependent on environmental conditions. To control this disease used registered fungicides. See figure 2.

Fig. 2. Blast

1.4 Brown Spot

The brown spot caused by the fungus it is also called cochliobolus Miya beans it is the most dangerous disease of rice crops in the world (see figure 3). It is affected by the rice leaf it has appeared on the rice leaf the spot may be very size and shape from brown to dark spot the larger spot is dark brown and the smaller spot is reddish-brown the fungus causes the oval shape of dark brown spot on the leaf. The damage can be reduced by maintaining the proper condition of crops through fertilization, land levelling, soil preparation, and drainage management seeds protect from fungicides and seed-borne fungus. When this disease attacked the rice field it may lose the grain of 60 to 90% [16]. The best control of this disease in the current environment scenario is to use different management approaches.

Fig.3. Brown Spot

1.5 Tungro

Rice tungro is caused by the combination of two viruses which are moved to rice hoppers as in figure 4. Leaf discolouration and stunted growth have happened when both viruses attacked the rice crop it also infects the cultivated rice. The symptoms of rice tungro are included the orange-yellow colouring of leaves it also affects the rice growth when this disease attacked the rice field it reduces 68% of grain [17]. Tungro infected rice leaves which become dark blue. Tungro is the most damaging and destructive disease when it appeared in an early stage of growth it will destroy the whole field of rice crop when Tungro is present in the field it spread all field rapidly and damage the young rice leaf. A noticeable situation occurred the rice leaf colour become yellow and orange-yellow. The discolouration begins from the top to the bottom of the rice plant. The mottled and striped appearance of infected leaves. This disease attacked plants when nitrogen and zinc deficiencies occurred and water stress, rat damage how to manage the rice plant farm Tungro disease it must be insecticides to control leafhopper.

Fig. 4. Tungro.

2 Literature Review

There are a lot of research papers that are related to Deep Learning technologies the Agriculture deep learning is very important to the health of crops and plants. The Deep learning base Agriculture system has used various approaches to manage the disease. Those affect the health of plants leaf. However many procedures to apply in the research paper to have been read to receive ideas to control the disease in plants and how the plant's growth is increased.

Wen Chen [11] has defined an efficient way to monitor the form for disease detection it uses IoT (Internet of Things) and A. I (Artificial Intelligence) to detect plant disease uses rice talk project and IoT devices to identify the rice-related disease, rice blast, and Tungro.

Matheus Cardin. Ferreira lima[12] has proposed a more efficient disease that occurred in the Agriculture system. It is applying IoT for automatic detection traps for smart Agriculture systems these techniques are very important to detect and affect disease on plants in too early stages. It used a sensor to automatically identify and monitor pests. It uses an infrared sensor, audio sensor, and camera for image capturing. It utilizes a trap and decision support system. The system has been designed and configured to improve Integrated Pest Management (IPM) Olalcunle Elijah [13] has described in his paper the smart Agriculture system using IOT techniques are wireless network system (WNS) radio frequency identification cloud computer and end-user applications. The usage of both IoT and data analytics (DA) to provide the operational efficiency of a smart Agriculture system. The wireless sensor sends the data to the cloud and former cell phone without any human interaction for the environment monitoring by deploying the wireless sensor network for the IoT Agriculture system

Robert [25] has defined the structure of the IoT system. It applies the PIR sensor and Motion sensor surrounding the plants to detect the moment of pests that are attacking the Plants. The smart pest repeller will do a function when insects are shown on or near a Plant and it detects the particular location of form when pests are detected where farmers spray the poison on particular places.

Luiso Lolong Lacatan [26] has proposed cloud-based farming for computer generation through a wireless sensor system his paper describes the low-cost IoT based Agriculture system which monitors the real-time plants' health through the use of a wireless sensor network to measure the moisture content, humidity, and temperature of plants soil and existing location of plants through the technology of global position system (GPS) in 3D three dimension street view satellite system.

S. Ramesh [27] has defined in his paper the pest damaging infrastructure and health of plants and spreading the disease to all farms. The farmers save the plant they must regularly visit the field approach to automatically detect the disease of Plants through the usage of remote sensing IoT techniques to identify the pest attacked on Plants. Remote sensing technologies are modern data-driven pest management techniques the wireless technologies can be used to transfer the data among farmer traps and cloud servers.

Adhao Asmita [28] proposed an automatic machine system to detect pest attacks on plants in their early stages. The system control and detect the disease on cotton leaf soil quality monitoring the system detect the cotton leaf disease and inform the farmer of particular remedies to spray on the cotton leaves in this system android app is utilized to display the plant's structure and show the humidity moisture and temperature using water level in the tank. The system has been developed through sensor and raspberry pi which created its independent and cost-effective system.

Apeksha Thorat [29] proposed that IoT provides the enhanced quality of Agriculture. IoT provides smart farming it consists of actuators and sensors that provide connectivity. The system detects the leaf disease on the server-based. The system monitors the humidity, temperature, soil, and moisture of the farm. It used the sensor network controlled by the raspberry pi controller. This paper provides the IoT techniques WSN, sensor, and Raspberry pi send the immediate status to the farmer or send to the cloud. This system is created through several wireless sensors like humidity and temperature. The GSM module is used for wireless communication. K. Lakshmi [30] proposed the automatic system that monitors plant growth this work has combined the image processing techniques and IOT techniques to identify the plant health and surrounding environment factors like humidity, temperature, and soil moisturizing. The system run pre-processing image techniques that are already stored in the database. That compares the leaf image like colour, shape, and texture of leaf any disease of the leaf is detected the system sends the message alert to the farmer to get the precautions against pest who damage the vast area of the field.

M.Singh [31] has defined in his research paper the early detection of disease in rice crops. Many algorithms can be utilised to detection of rice plant leaf disease by image processing techniques in the work he developed IOT-related infrastructure to provide a field disease detection system. The IoT system change the Agriculture system the farmers got real-time monitor the plants and observed the temperature and water level in the field through the deployment of technologies the IoT system addressed the problems related to Plants.

Shaikh et al.[32] presents the contemporary approach for object recognition by the fusion of low-level features and spatial layout. Low-level features are very important for content-based image retrieval, further Hussain et al., [33] discussed an innovative idea for the segmentation of connected characters in the text-based CAPTCHAs for character recognition. The plan of work is explained. Kehar et al. [34] decoded partially connected characters with background clutter in a text-based CAPTCHA scheme.

3 Material and Method

The proposed AI-based model for rice leaf disease detection uses You-Only-Look-Once (YOLO) neural network to detect four plant diseases. Our approach uses different data pre-processing and augmentation tools to clean the data and convert it into a suitable form to train the network. Our approach follows the below steps as depicted in the following flowchart, figure 5.

3.1 Dataset

This is an annotation tool that assists in labeling the images present in the dataset. The tool helps to annotate the datasets easily according to the format required by any neural network. It has features of Deep Learning and testing of particular objects the dataset created through labelImg is deployed on Yolo.

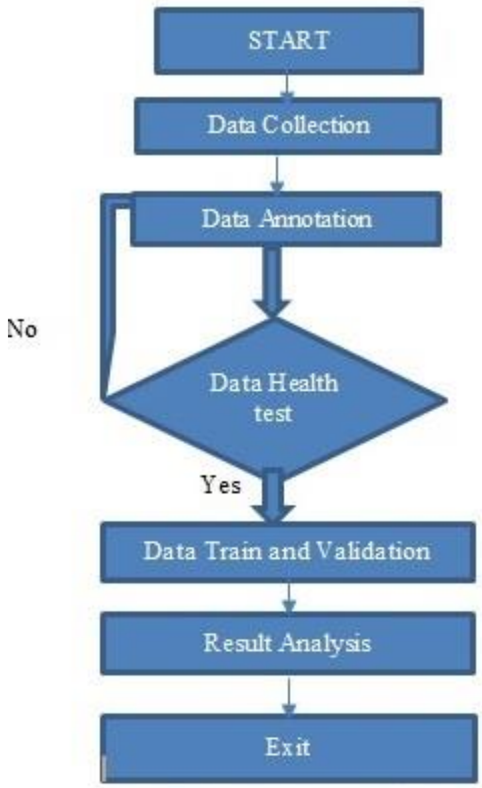

Fig. 5. Main Flow Chart

The labelImg converts the multiple objects into pictures and gets the size location of objects and classes automatically. It helps to draw rectangular boxes around the rice leaf objects. It is necessary to labelling on images for computing vision there are many other tools used for labelling, but it is easy to configure, implement and test it is free of cost tool which is compatible with Yolov5. It is easy to deploy and lightweight software. Once the installation has been completed, open the labelImg/ Data directly and find the pre-defined data in the data folder and change the name of the class which we utilize in the app. our project is rice leaf disease detection this is the following look of our data classes.

Open labelImg tool and label the images with the correct annotation. Once it is done, then select the first image of the folder which is ready for annotation (see figure 6). Before labelling on images first select the Yolo mode of LabelImg. Create a rectangular box from the left panel and square around each rice leaf disease image. Try to cover the rice leaf image affected area with label and do not leave the affected area of leaf into square every time create rectangular box appear on image to cover the square at the last we developed the rice leaf image label completely. The right side of the panel shows the image class names. In labelImg tool, the .txt file is linked with a particular image.

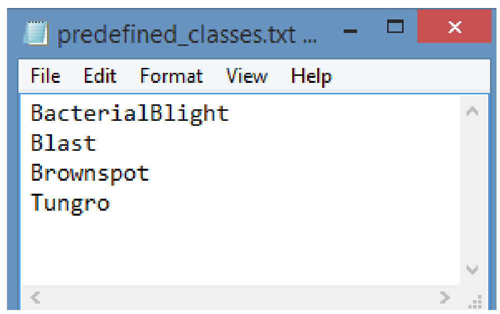

Fig. 6. Pre-defined Classes

The above figure of the dataset includes four classes.

3.2 Roboflow

The Roboflow is a computer vision plate form that is used for data collection data training and pre-processing data as in figure 7. The Roboflow has a lot of features it is used a public dataset and its custom dataset. The Roboflow has several annotation techniques it used pre-processing technique to image resizing, orientation, and contrasting.

Fig. 7. Data Pre-processing

3.3 Data Augmentation

Data augmentation in computer vision is playing an important role (as shown in figure 8). It is a forefront state-of-the-art model. For Yolov5 image detection utilize several techniques of data augmentation, the Yolov5 depends on several images and object classes. Data augmentation is used to increase the performance of the model it is very essential for computer vision datasets. It improves the downstream performance of custom datasets, data augmentation includes the cropping, rotating, adding noise, and flipping of the image. Augmenting on images used for creating a larger dataset that is best for a project, different augmentation techniques are applied to several scenarios. For data augmentation, we used Roboflow it is easy to use to upload the image for augmentation and download our augmented images in any format and improve the fit model.

Fig. 8. Data Augmentation

3.4 Yolo Architecture

The Yolo model is a swift object detection model it has good performance related to its size and it has been regularly improving [2-3]. The Yolov5 is the latest version of Yolov4. The Yolov5 repository is an extension of Yolov3. Yolo5 is faster than its previous versions such as Yolo4 and Yolo3 as discussed in [35]. It is easy to use, configure, implement and test still significant research occurred on Yolov5. A Yolo is a real-time object detection model where these objects are either videos or images the Yolov5 identifies and classify the images it can also detect multiple images within an object. The Yolo came in 2015 it has a huge speed for making real-time object detection.

This is an object detector is designed to get an input image and develop and feed features of an image through a prediction system and draw bounding boxes surrounding the image and predict the classes [4-5]. This is an object detector to combines the bounding boxes with the class's labels in several networks. Yolo Network depends on three Parts: (1) Backbone: CSPDarknet, (2) Neck: PANet, and (3) Head: Yolo Layer. The data are first input to CSPDarknet for feature extraction and then fed to PANet for feature fusion. Finally, Yolo Layer outputs detection results (class, score, location, size), as shown in figure 9.

3.4.1 Backbone

A CNN that aggregates and creates image features in several systems. It is composed of different pieces.

3.4.2 Neck

There are many layers to collect and mix images and transfer these images' features to prediction.

3.4.3 Head

It takes bounding boxes and class features for prediction.

3.5 Yolo Training Procedures

The object detection model has been made through Training. The training is crucial for an object detection system

3.5.1 Loss calculation

The constituent loss function is used to calculate the loss function of Yolo to improve the efficiency of the model by increasing its recognition rate. It also calculates the loss of class, object and GIou losses. It is developed to maximize the mean average precision of object recognition.

3.5.2 Precision and Recall

The precision is the ratio which defines the true positive (TP) and the sum of true positives and false positives (FP) as given in the below equation.

Precision = TP / TP + FP

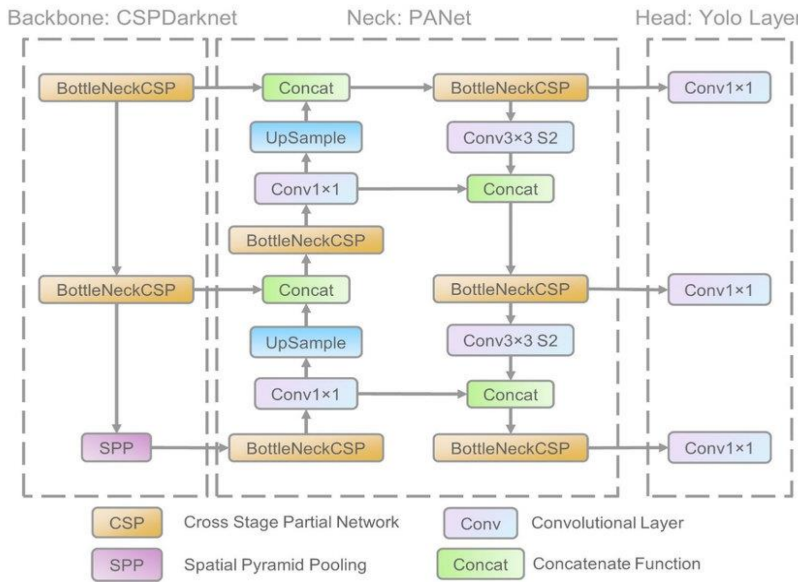

Fig. 9. The network architecture of Yolov5.

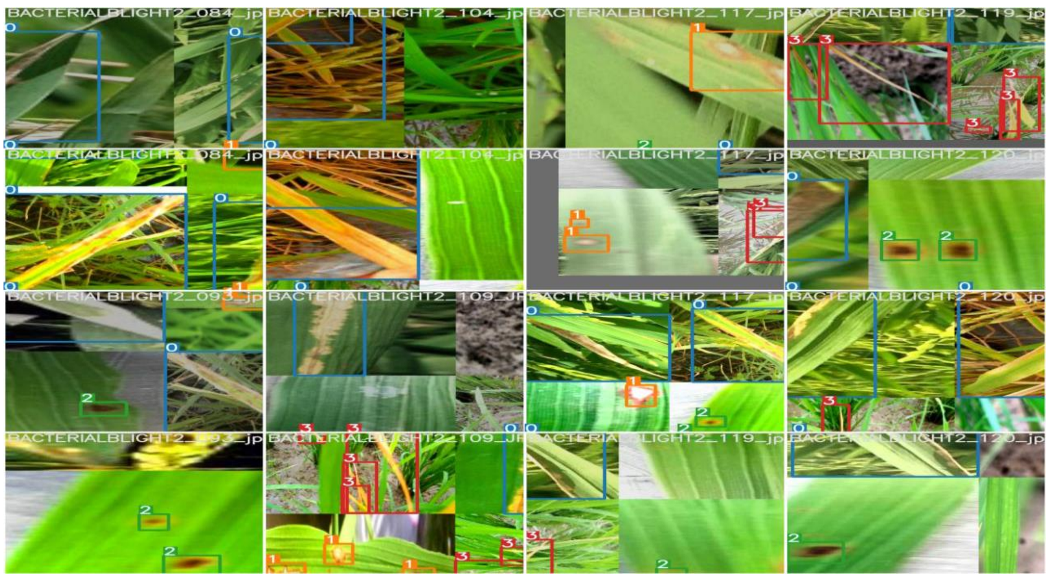

Fig. 10. Train image.

For example, 20 plant images were uploaded into the model. The model detects 100 plant images. The model has 100 plants these 20 plant images and bounding boxes are drawn around every plant image of the dataset.

The calculation of precision of this model is to check the 100 plant bounding boxes if it had 20 incorrect from 100 plant images then the precision value is 80/100=0.8. The recall metric is the ratio of true positive (True predictions) and the total ground truth positives (total number of rice plant images).

Recall=80/120=0.667.
The recall measure detects all objects in the data.

4 Experimental Results

Train image 0 value of blue boxes denote the Bacterial Blight disease, 1 value orange boxes denote the Blast disease, 2 value green boxes denote the Brown Spot disease, and 3 value red boxes are used for Tungro rice leaf disease, respectively as shown in figure 10.

Test image shows the label and prediction values respectively, Blue colour boxes denote the Bacterial Blight disease, which is detected with a confidence score of 0.6, Orange colour boxes show the Blast rice leaf disease, Green colour boxes show the Brown Spot Disease and Red colour boxes shows the Tungro disease with respective confidence scores. The above bounding box values of different rice leaf diseases show the prediction values of the model for the recognition of various plant diseases, see figure 11.

Precision is a ratio between the numbers of positive results and predicated by the classifier in the precision figure 12. The detection model is performing well because the precision values are increasing in all colour boxes. The average confidence value is 0.832. In figure 13, recall shows the average value of the four classes is 0.94.

Fig. 11. Test image.

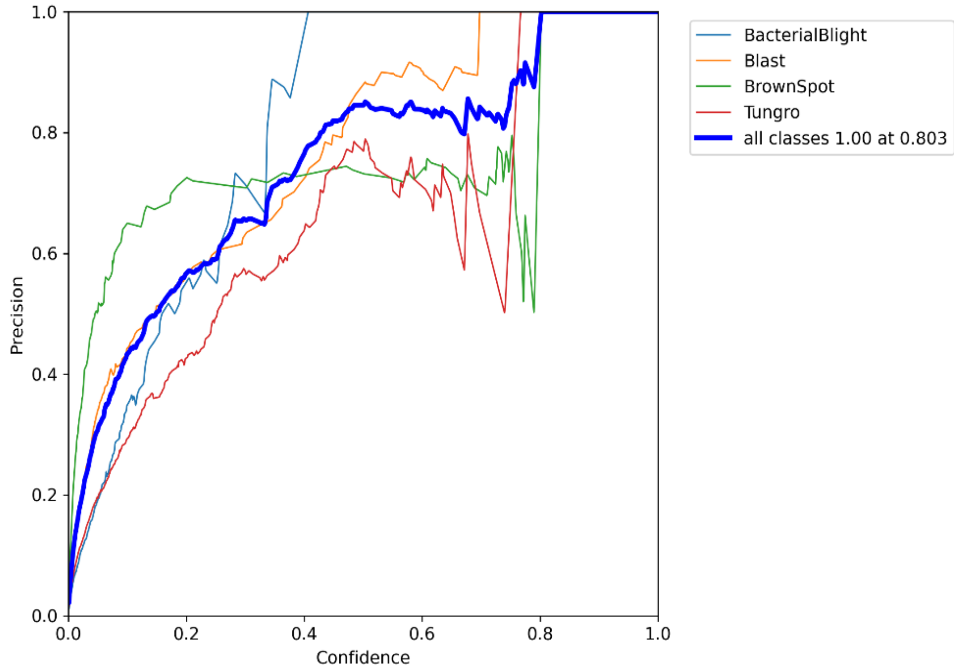

Fig. 12. The precision of model recognition

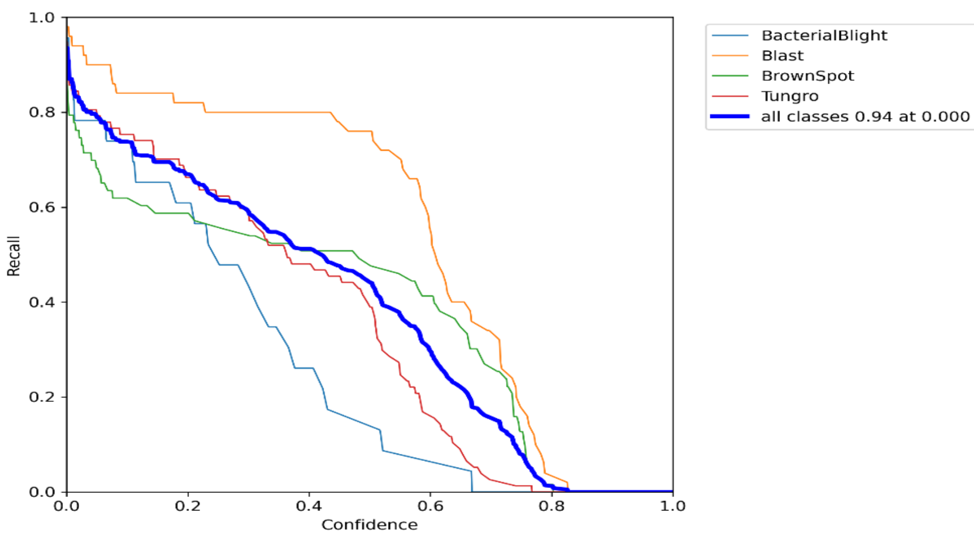

Fig. 13. Recall of model recognition.

Precision and recall (as shown in figure 14), this is a combined graph of precision and recall where bacterial blight value is 0.58, Blast rice leaf disease value is 0.809, brown Spot value is 0.554 and Tungro rice leaf disease value is 0.535, the average values of four classes are 0.602 and mAP value is 0.5 which is a better result. Figure18. precision and recall, this is a combined graph of precision and recall where bacterial blight value is 0.58, Blast rice leaf disease values are 0.809, brown Spot value is 0.554 and Tungro rice leaf disease value is 0.535, the average values of four classes are 0.602 and mAP value is 0.5 which is a better result.

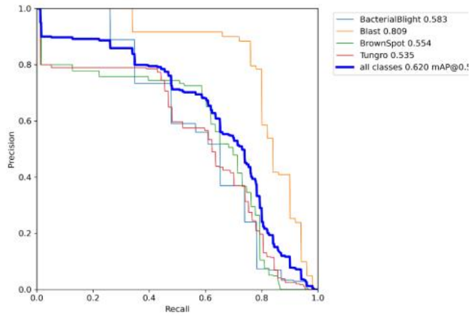

Fig. 14. Precision and Recall of model recognition.

The f1 score is the weighted average of precision and recall see figure 15. The f1 score is calculated based on values of both false positive and false negative. Our model attains an f1 score of 0.62, which shows that model has achieved considerably better performance than the existing rice leaf disease detection methods.

The overall performance of the rice leaf disease detection model is shown in figure 16. The result shows that the model has exhibited accurate performance in recognizing the various rice leaf diseases with suitable confidence scores. The model recognized rice leaf objects with 100 epochs. Our proposed approach classifies the diseases with recall, precision, and mAP score of 0.94, 0.83, and 0.62, respectively.

5 Conclusions and Future Work

In this research paper, the deep learning model of Yolov5 is discussed and used for rice leaf disease detection. The model of Yolov5 is trained on an image dataset of four rice leaf diseases with 100 epochs. The trained model is tested on unseen images of rice leaf diseases. The model has achieved quite a better recognition rate with the highest precision, recall, and mAP. In future work, this model may be used for real-time object detection by deploying the proposed approach on the smart embedded system to assist the farmers in the agriculture field to improve crop productivity

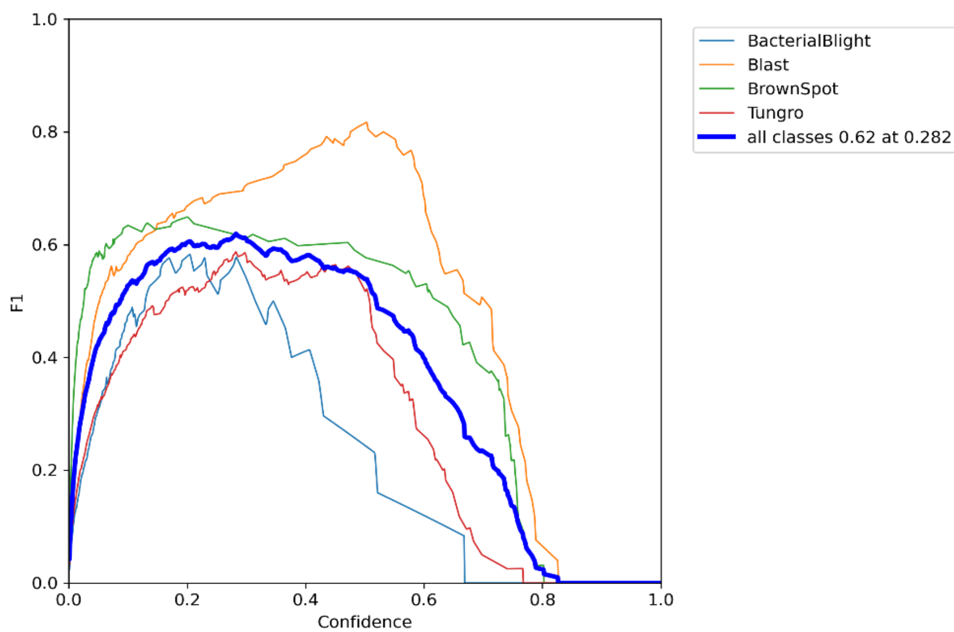

Fig. 15.The weighted average of Precision and Recall.

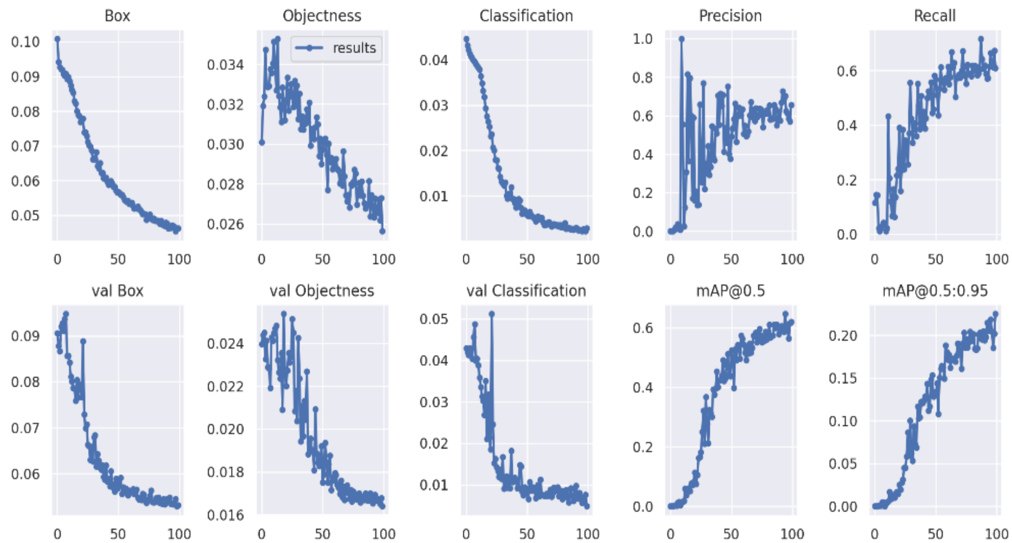

Fig. 16. Results

AUTHOR CONTRIBUTION

All authors contributed equally to the work.

DATA AVAILABILITY STATEMENT

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

FUNDING

Not applicable.

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