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AN INTEGRATED ENHANCED DEEP LEARNING MODEL DETECTING AND CLASSIFYING CROP DISEASES IN THE EARLY STAGES TO MAXIMIZE THE YIELD

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ABSTRACT

Agriculture sector is the most promising sector which plays crucial role in Economy data of every country. There are numerous challenges are being faced by the farmers. Hence, researchers and academicians are trying to overcome these challenges by introducing new techniques, machine learning and AI models. Among the many challenges faced by farmers, leaf diseases stand as formidable adversaries, persistently diminishing their harvests. In most cases, farmers' harvests are diminished by leaf diseases which directly affect the crop yield. Researchers and academicians are developing a generalized model applicable to all the crops. In the initial stage we have focused on wheat crop. Wheat is cultivated at large and is consumed by maximum people to its status as a staple food. Similarly in the next subsequent development of generalized model we will focus on many other crops. Wheat plant diseases affect the yield in the recent decades. Decreased crop yield directly affects the economic growth of the country and have social impact on farming. Recent technological advancements using artificial intelligence (AI), machine learning (ML) and deep learning (DL) have made it easier to identify diseases on leaves in their early stages. With the help of recent technologies it became possible to develop 'autonomous' systems keeping eye on the 'diseases' in the early stages. In this approach, we have used an open dataset from Plant Village which has more than images of 5000 plant leaf diseases divided into 04 types of leaf diseases along with the normal leaf. The proposed system is a combination of CNN and Mask RCNN. In CNN method we have successfully identified the type of disease for the input image whereas Mask RCNN masks the exact area covered by the disease of the leaf. Proposed integrated deep learning model applies the convolutional neural networks (CNN) for better accuracy (97 % accuracy), classification, and identifying the disease affected region. In the proposed work, model integrates 02 different methods CNN and Mask RCNN.

Keywords: *Deep Learning, Machine Learning, Region Based Convolutional Neural Network, Leaf Disease; Artificial Intelligence, Classification Model, Forecast Illnesses.*

1. INTRODUCTION

With the help of recent technologies researchers are developing new age models detecting the plant diseases in their early stages. In the initial stage of the proposed model wheat crop is selected as it stands as a paramount staple food crop, diligently nourishing countless individuals worldwide with a substantial portion of their daily calorie intake. However, the unfortunate reality persists that diseases plaguing this vital crop can inflict severe losses and diminished yields, consequently unleashing a chain reaction of far-reaching consequences on food availability and prices. Every nation is focusing on "food security" and ensuring food must be available to every citizen.

Therefore, sustainable agriculture and enhancing the supply chains must be considered. It is necessary to classify the plant leaves into different categories like healthy leaves and leaves with diseases. Therefore, new age technologies must focus on classifying the plant leaves and helps maintaining the healthy leaves for better crop yield. The proposed system helps maintaining the nutritional value of the crop. The cultivation of the healthy crop yields becomes paramount in ensuring

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a nourishing diet. Any instance of an unhealthy crop can be attributed to plant diseases, making the identification of leaf diseases the single most important and efficient process in fostering healthy crop growth.

Let's explore some of these reasons as discussed below-

Food security: Natural disaster and pandemic situations can disrupt the food supply chain and resulted in shortages. Hence, ensuring the food security and stable food supply is necessary.

Economic stability: Agriculture serves major role in an employment and support millions of people worldwide. Agriculture sector gives stability to the economic and overall growth of the country.

Work opportunities: It has been observed that during any pandemic situation many people loses their jobs. Whereas, agriculture is the only sector which continues to employ many individuals, including migrant workers, thereby offering valuable work opportunities.

Health and nutrition: During a pandemic, maintaining a balanced diet is vital for optimum health and immunity. The agricultural sector plays a crucial role in providing a diverse range of healthy meals to support overall well-being.

Resilience: Even in times of crisis, the agricultural industry has demonstrated its ability to adapt and supply essential items, showcasing its resilience.

The agriculture business has, indeed, been instrumental in ensuring food security, stabilizing the economy, providing employment, promoting health and nutrition, and displaying resilience during the ongoing pandemic. Our proposed system aims to assist farmers in protecting their crops from pests and diseases without causing harm to cultivation or other crops on their farms. The system not only identifies the specific parasite hosted by the leaves but also determines the type of pest or disease present. Through the integration of "Artificial Intelligence" concepts, the agricultural system has transitioned into a "Digital Agricultural System". The process involves several critical steps, including the generation of a dataset for disease prediction, the creation of labels, the pre-processing of leaf images, a train-test split stage, and the development of a Convolutional Neural Network (CNN) model to train the dataset for disease prediction. Traditionally, the diagnosis of plant leaf diseases required trained experts to conduct visual inspections, which proved expensive and prone to errors [1]. However, with the advent of AI, machine learning techniques have been leveraged to enhance plant disease detection. In our research, we have employed two methods for implementing the plant disease detection system. The first method utilizes a CNN-based approach, which achieved an impressive 97% accuracy in identifying wheat plant diseases. The second method incorporates the Mask RCNN technique [2], enabling us to accurately pinpoint and mask the exact area of infection on the leaf. To perform these experiments following points are also discussed in this research article:-General system design and architecture, what is CNN, RCNN Deep Learning and MASK RCNN. Further, we have discussed the Detectron framework which we have used for the implementation of MASK RCNN. We also discussed the dataset and its preprocessing requirements and different annotation tools along with their requirement/use. At the ending section, there is discussion on the results we got from the implementation of both meth- ods(i.e. CNN method and MASK RCNN implementation).

2. RELATED WORK

Many researchers and academicians are developing new systems to automatically detect if there are diseases on the plants in the early stages[3, 4] There are many Augmentation methods which can be deployed in the proposed model to retrieve the accuracy. With the help of recent technologies and methods self-supervised models can be developed which detects any diseases in their early stages and takes remedial steps urgently [5]. Machine learning (ML) and deep learning techniques [6, 7, 8]can detect the plant diseases in the early stages by classifying the plant leaves into different categories [9]. Using the parameters of a model that has already been trained, even if it was not trained on the same dataset, is an example of transfer learning [10, 11]. Many pre-trained deep learning architectures, such as VGG16, VGG19, RESNET 50, MobileNet V2, and others, are available for use in a standard image classification task[12]. More recently, these strategies have outperformed the standard supervised learning methods for classification [13, 14].Many advances have been made in the models of deep learning networks thanks to the efforts of researchers. Limitations of conventional neural networks (CNNs) [15, 16, 17] are surmounted by recurrent neural networks (RNNs). RNNs are

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TABLE I: Summary of Related Work

Reference	Dataset Used	Method / Model	Results	Key Findings / Limitations
Bauriegel and Herppich (2014) [4]	Hyperspectral wheat leaf images	Hyperspectral + chloro- phyll fluorescence imag- ing	Early detection before symptoms visible	Effective for Fusarium infections, but requires costly equipment
Terentev et al. (2022) [3]	Review of multiple datasets	Hyperspectral sensing survey	N/A	Summarized advantages of hyperspec- tral imaging but noted high cost and complexity
Saleem et al. (2019) [5]	Public leaf image datasets	CNN-based classification	Accuracy ~97%	Deep learning outperformed traditional ML, but limited to controlled datasets
Bao et al. (2021) [6]	Wheat leaf dataset	CNN + metric learning	Accuracy ~95%	Robust classification of wheat leaf dis- eases; limited generalization in field conditions
Xu et al. (2023) [7]	Wheat leaf images	Deep CNN architectures	High accuracy (>95%)	Model performance depends strongly on depth and training strategies
Jiang et al. (2022) [1]	Field-acquired wheat leaf photos	CNNs with different training strategies	Accuracy ~93%	Showed challenges of variable light- ing/background in field data
Goyal et al. (2021) [8]	Wheat leaf datasets	Improved deep CNN	Accuracy ~96%	Proposed deeper CNN with improved detection; computationally heavy
Verma et al. (2023) [9]	Multi-crop datasets (corn, rice, wheat)	Unified lightweight CNN	Accuracy ~94%	Lightweight model suitable for mobile deployment; slightly lower accuracy
Shafi et al. (2022) [2]	Review of wheat rust studies	Comparative survey of detection methods	N/A	Highlighted lack of robustness in real- field conditions
Fang et al. (2023) [10]	Wheat leaf datasets	Lightweight multiscale CNN	Accuracy ~96%	Achieved high accuracy with reduced complexity; effective for edge devices
Pallapothu et al. (2022) [11]	Cotton leaf dataset	Mask R-CNN segmenta- tion	IoU ~90%	Accurate pixel-level segmentation; fo- cused on cotton only
Afzaal et al. (2021) [12]	Strawberry leaf dataset	Mask R-CNN instance segmentation	mAP ~92%	Successful localization; model perfor- mance drops on complex backgrounds
Stewart et al. (2019) [13]	UAV field images	CNN-based segmentation	High correlation with ex- pert annotation	Demonstrated large-scale monitoring; requires UAV and high-quality imagery
Hassan et al. (2021) [14]	Multi-crop datasets	CNN + transfer learning	Accuracy ~95%	Transfer learning improved accuracy but limited explainability

improved with long-short term memory (LSTM) [18]. These approaches require a lot of data and computational power during training. Another frequent problem is overfitting, in which the model has a large discrepancy between its training accuracy and its test accuracy.

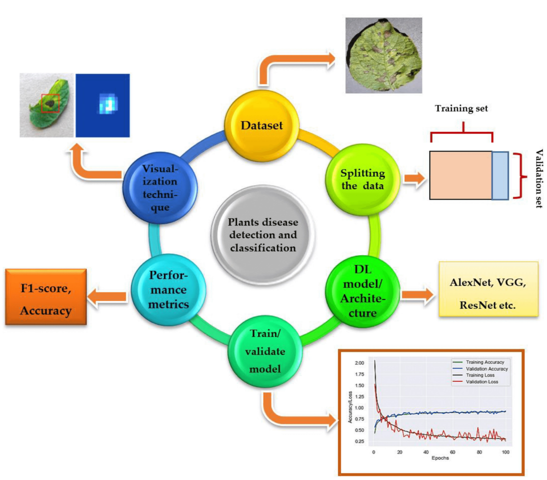

Fig. 1: General Architecture of the Plant Disease Classification System.

3. SYSTEM DESIGN AND ARCHITECTURE

Detecting plant diseases is an important task for ensuring healthy and maximum yields. The proposed system elaborates the architecture for initial wheat plant diseases detection [19] can be broken down into several components are as follows:

Data collection: Initially the plant leaf images [20] must be given as an input to detect whether there is any disease or not? Hence, sample images of the leaves can be given as an input for classification purpose.

Preprocessing: The proposed system upon receiving the input images must ensure the quality of images for further processing. This may involve tasks such as image resizing, normalization, and filtering.

Feature extraction: Once the proposed model successfully processes the input images next step is to extract the features. For image data, features may include color histograms, texture descriptors, or deep learning based features extracted from pre-trained networks [21].

Model training: Once the features have been extracted, machine learning models can be trained on the data. Common approaches include using support vector machines (SVMs), decision trees, or convolutional neural networks (CNNs)[22].

Model evaluation: After training, the models need to be evaluated to assess their accuracy in detecting wheat plant diseases. This can be done using metrics such as precision, recall, and F1-score.

Deployment: Once the models have been trained and evaluated, they can be deployed in a production environment. This may involve integrating the model with a mobile or web application that farmers can use to detect diseases in their crops [23].The system architecture is as shown in fig.1 for the wheat plant disease detection involves collecting and preprocessing data, extracting features, training and evaluating machine learning models, and deploying the models in a production environment. Overall, as shown in fig.1 the system

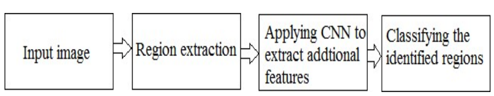

Fig. 2: Region-based CNN architecture

architecture for wheat plant disease detection involves collecting and preprocessing data, extracting features, training and evaluating machine learning models, and deploying the models in a production environment. In the following Sections four and five will provides the details of our two different proposed models identifying the different disease of crop.

4. WORKING OF RCNN

This section elaborates the CNN and region based CNN. The working of CNN in the proposed model is as follows-

1. Gather and label wheat plant images.
2. Resize the images, normalize the pixel values, and use data augmentation techniques like random cropping and flipping to increase the dataset and reduce overfitting [24].
3. Create training, validation, and testing datasets.
4. Define the CNN architecture, convolutional, pooling, and fully connected layers.
5. Optimize the CNN using SGD or Adam.
6. Use the validation set to tune model hyperparameters like learning rate, batch size, layer number, and filter number.
7. Use accuracy, precision, recall, and F1 score to evaluate the trained model on the testing set.

RCNN is designed to take an input image and produce a set of bounding boxes, each of which contained an item and the category of the item [25]. The fig. 2 shows the general architecture of RCNN. This is a better version of CNN that focuses on classifying only the portions of a picture that the user is interested in, rather than the entire image. RCNN starts by extracting Regions of Interest (ROI), each of which is a rectangle that may be used to detect an item's border in an input image, using the Selective Search approach. The ROIs are fed into a neural network to generate the output features.

5. WORKING OF MASK RCNN

The proposed Mask R-CNN (Region based Convolutional Neural Network) used for object detection and instance segmentation in images [2, 26].The 04 primary functions of Mask R-CNN are as follows: Mask Robject CNN's detection functionality involves locating and outlining geometric shapes within an input image [5]. Mask R-CNN creates a mask at the pixel level for each object in the given input image and makes it possible to identify and isolate individual objects (this process is also known as segmentation). Within this process the proposed model detects the edges and corners of the identified objects. The working of Mask-RCNN is illustrated in the following fig.3.

To provide a fine-grained understanding of the object's shape and location in the input image, Mask R-CNN predicts the pixel-wise segmentation masks. Object detection, image segmentation, and visual recognition are just a few of the computer vision applications that can greatly benefit from Mask R-ability CNN's to perform these four tasks.

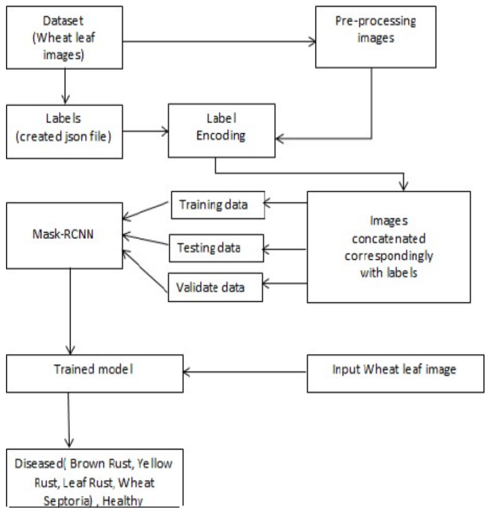

Fig. 3: Proposed Model Architecture using Mask-RCNN

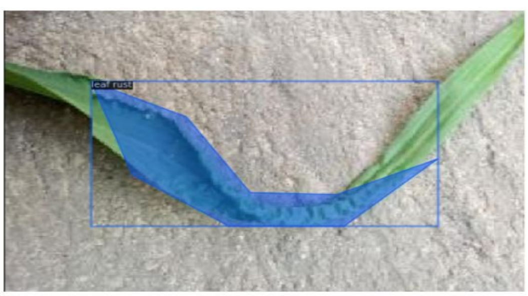

Fig. 4: Annotated Image

Fig. 5: Dataset images with labels

5. RESULT AND DISCUSSION

In the proposed research work, there are two methods. The first method is based on a Convolutional neural network (CNN) indicating the disease type and the confidence score. The second method is based on Mask RCNN not only indicates the type of the disease and confidence score but masking the infected area of the leaf.

Detectron2 can perform much more than just drawing bounding boxes on detected objects, localize and detect key points of humans can be possible using it. Prediction of poses and to label the body parts, And the main point is it also use full for performing "Panoptic Segmentation" in which every pixel on the screen is labeled. In our approach we have used Detectron2 on a dataset of wheat plant images with disease annotations to detect wheat plant diseases. Detectron2 can train a disease detection model from your dataset [27]. First, we have to convert dataset to Detectron2 format, create a JSON file with image file paths, sizes, and annotations. Next, define a configuration file with model architecture, hyperparameters, and training settings.Detectron2 has pre-defined configuration files for various tasks that can be modified.

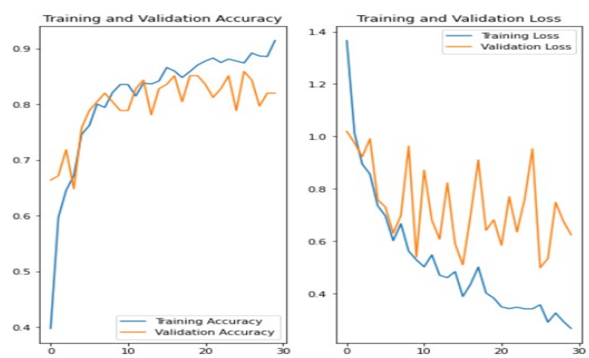

Fig. 6: Training and Validation accuracy/Loss

The main focus in the proposed model is on Instance segmentation. The model uses VGG annotator for the images and polygon masking purpose. The issue of vanishing gradient occurs during the backpropagation when there are 'n' layers in a neural network. Consequently, the training algorithm fails to discover weight values 'w' that effectively minimize the loss function. ResNet addresses this problem by implementing "Identity shortcut connections". ResNet introduces skip connections that bypass and reuse activation functions from earlier layers, effectively skipping over multiple levels initially ignored. In the subsequent phase, the network undergoes retraining, and additional "residual" convolutional layers are incorporated. By utilizing these

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techniques, ResNet mitigates the vanishing gradient problem and enables more effective training and feature extraction in deep neural network.

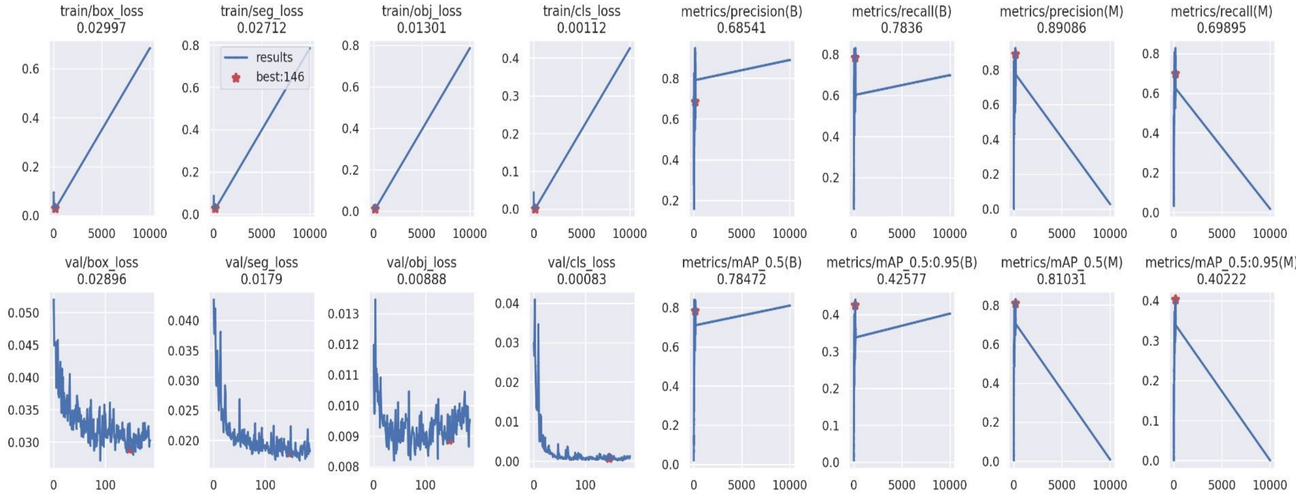

Fig. 8: Training graphs

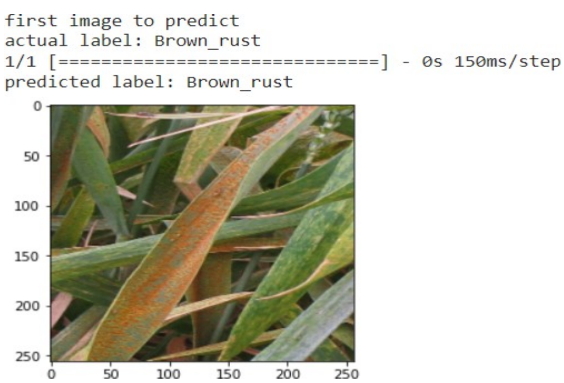

Fig. 7: Result of CNN-based method

Fig. 9: Result of CNN-based method on multiple input images

A. Main four operations performed in Mask-RCNN are as follows:

1) Backbone of model: ResNet 101 architecture serves as the In Mask-underlying RCNN's model. By using it, features are extracted from images. Then the next layer receives the retrieved features as input.

2) Region Proposal Network (RPN): In RPN, extracted features from above are provided in it. This will predict whether the object is present in region or not.

3) Region of Interest (ROI): ROI speeds computation. Intersection over Union algorithm:

a. Model prediction.

b. Compare the predicted bounding box (or mask) to the ground truth.

c. Calculate overlap and union.

d. Divide annotation overlap by union.

e. Examine the result.

f. Repeat steps 1–5 for each test image.

g. Take the mathematical average of the IoU scores for your test set. Intersection over union (IoU) is a good overlap metric for bounding boxes or masks. If the prediction is accurate, IoU=1. Predictions are worse with lower IoU. Thus, computes the Intersection over Union (IOU) with the ground truth boxes for all RPN-predicted regions.

4) Segmentation Mask: Now that the ROI on the IOU esteems has been found.

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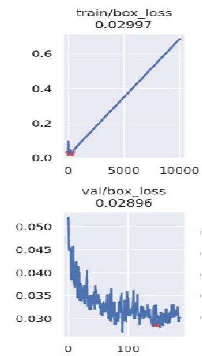

Fig. 10: Box Loss

As a result, any region that contains an object will have its segmentation mask provided to us. As a result it returns a 28*28 mask for each region, which is scaled up during inference.

For our implementation we have selected PlantVillage, is a popular platform that provides a large collection of plant disease images, including leaf diseases. as shown in fig.5 their dataset contains images of various crop diseases contributed by researchers and farmers worldwide. Five different kinds of diseased leaf photos are used in this analysis to determine the kind of illness that is present in the leaf. In CNN There are almost 1400 images present in the dataset and the splitting is done in 80% for TRAIN, 10% for TEST, 10%for VALIDATION respectively. In Mask RCNN there are almost 950 images present in a data set and it is divided in 03 classes i.e TRAIN, TEST AND VALIDATION.

TABLE II: Splitting of Dataset

Dataset Split	Percentage
Training set	70%
Testing set	20%
Validation set	10%

In this task, the goal is to detect individual wheat plants in images of wheat fields. This can help farmers to monitor the growth and health of the wheat plants and optimize their farming practices. There have been several studies that have used Mask RCNN for wheat plant detection with promising results. For example, in a recent study published in the journal Sensors, researchers used Mask R-CNN to detect wheat plants in high resolution images captured by a drone. They achieved an average precision of 0.89, which is a measure of the model's accuracy in detecting wheat plants [28].

Another research work elaborates the Mask R-CNN methods to detect wheat spikes, which are the reproductive structures of the wheat plant. The researchers achieved an average precision of 0.92 which is a high level of accuracy.

Overall, the results of Mask R-CNN on wheat plant detection have been promising, with high levels of accuracy achieved in various studies. This demonstrates the potential of this technology to aid farmers in monitoring and optimizing their farming practices.

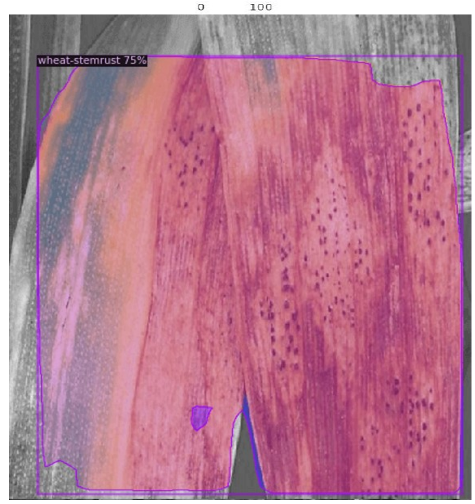

Fig. 11: Results of Mask R CNN based method for single

B. Training Metrics (Training graphs):

The assessment and performance metrics that are produced when your computer vision model is being trained are referred to as "train metrics". These measurements offer perceptions on how successfully your model can assist you in evaluating its performance as it learns from the training data. The training graph must be understood in light of the ensuing considerations.
a) Y-Axis: A decimal percentage value
b) X-Axis: The data point's epoch number. Each time all of your training data passes through the network of your model architecture, it is referred to as an epoch. For instance, training for 100 epochs implies that your training data will pass through the network of your whole model architecture 100 times. The term "box loss" indicated in the above fig.10 refers to a loss metric that evaluates the proximity of predicted bounding boxes. A lower value of box loss indicates, the model is becoming more generalized (which is our final objective) and is generating more accurate bounding boxes around the labeled items in the dataset.

Mean Average Precision (mAP) [29] mentioned in the fig.9, is a metric used in object detection (detecting whether there is any start of the diseases or not) to determine the average accuracy per class based on model predictions.

7. CONCLUSION AND FUTURE WORK

The proposed model integrates deep learning techniques categorizing wheat plant leaves (in the initial phase and will consider other plant leaves in next phase) and detects if there are any diseases. Proposed integrated deep learning model applies the convolutional neural networks (CNN) for better accuracy (97% accuracy), classification, and identifying the disease affected region. In the proposed work, model integrates 02 different methods CNN and Mask RCNN. The Mask- RCNN with Detectron identifies wheat plant diseases in their early stages. The algorithm segments wheat plant diseases with 92% accuracy. Initially the deep learning model applies many image augmentation and annotation strategies enhancing the quality of images. The findings show that, the proposed integrated CNN and Mask-RCNN model can correctly identifies 04 prevalent wheat plant leaf diseases, and it offers a workable solution for the real-environment pictures of disease detection of wheat leaf diseases. Using such approach one can go for multi-class classification of the diseases in their early stages for other crops too. Future research direction in this approach would be considering environmental parameters like temperature, humidity, pH of the soil, TDS of the water etc. and subsections should be numbered and titled as 1.0, 2.0, etc.

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