



# Classification of Plant Leaf Diseases using Object Detection Models: YOLOv5 and YOLOv8

Komma Tejaswi<sup>1</sup> and Venkata Ratnam Ganji<sup>2</sup>

M.Tech Student, V K R V N B & A G K College of Engineering, Gudivada, India.<sup>1</sup>

Associate Professor, Department of CSE, V K R V N B & A G K College of Engineering, Gudivada, India.<sup>2</sup>

**Abstract:** Traditional methods of diagnosing plant diseases are mainly based on expert diagnosis which easily causes delay in crop disease control and crop management. Due to the problems of many target areas and similar target types in the process of plant disease detection, the identification accuracy and speed are required to be high. Therefore, it is necessary to optimize and improve the existing methods (CNN, RCNN, Fast RCNN, Faster RCNN, and SSD) to meet the detection needs. So, we came up with a deep learning-based approach to identify the plant leaf diseases and classify the diseases using object detection model called YOLO. There are different versions of YOLO, proposed in the recent times, in that YOLOv5 model is considered one of the best models and the other is the recent version, YOLOv8 which was proposed in 2022. So, in this paper we compared the two models of YOLO, YOLOv5 and YOLOv8 on the same dataset, and found that for the dataset used the YOLOv5 model was found to be the better model with a mAP of 0.63, while the YOLOv8 model has mAP of 0.52. This study proposes that YOLOv5 model is suitable for plant disease identification tasks by comparing it with the latest version of YOLOv8 model which was proposed in 2022. To make the YOLO model to be better it can be optimised and the transfer learning ability of the model can be used to expand the application scope in the future.

**Keywords:** Deep Learning, Convolution Neural Networks, Transfer Learning, Disease Classification, Object Detection.

## I. INTRODUCTION

Food is considered the important part of our life. Good food is important for good life. So, in order to produce good food, the early detection of plant diseases is important. Annual global agricultural losses from diseases and pests amount to US\$250 billion. In 2021, the area affected by major diseases and pests in China reached 400 million hectares. Therefore, early detection of plant diseases in agricultural production is crucial. One of the most effective solutions is to predict and classify crop diseases by collecting crop growth images and building a detection model, which can provide fast and effective alerts and responses in agricultural production, improve disease control efficiency and reduce losses from agricultural diseases. The traditional method of diagnosing disease is mainly based on evaluating the nature of the health or disease of the culture. It directs agricultural production by manually observing the colour, size, and shape of pathological spots on crop leaves, leading to problems such as high labour demands, long diagnosis times, and low labour productivity. Building on this, researchers are working on identifying plant leaves and other traits using network models to achieve rapid detection and classification of diseases. At the same time, they continue to expand the types of datasets to improve the reach of the method, which plays an important role of reference and guidance in terms of quality and results. An early method of extracting traits from plant leaves involved manually extracting trait maps. Researchers extracted information about the properties of the segmented images, distinguishing them from anomalous situations. These methods usually require practitioners to extract occupational traits (such as numerical leaf traits, textural traits, and SIFT traits) and diagnose diseases. The modelling process is complex, the application difficult, and the applicability of the method still needs to be improved. Therefore, traditional methods cannot detect diseases and classify crops well. Object detection technology has become one of the current research fields based on the above problem. The technology classifies and defines the category of the object by object localization to complete the detection, positioning and classification of objects in images or videos. In November 2015, Redmond et al. the YOLO model. Recognition speed, accuracy, and pattern recognition class have been improved by using Dark Net for postfold feature detection and using less than a billion floating point operations (Flops)[5]. Based on the YOLOv4 model tessellation data improvement method, in June 2020, Ultralytics added new improvement ideas and developed the YOLOv5 model, which can flexibly control the model size by adding the Hard wish trigger function [6]. By improving the speed and accuracy of the model, the memory consumption of the model is greatly reduced, which satisfies the needs of this study. Based on the above comparative analysis of the performance characteristics of different types of detection algorithms, this study proposes a YOLOv5 model suitable for plant disease identification tasks by comparing it with the latest version of the YOLOv8 model proposed in 2022 [7].



## II. RELATED WORK

The advancement of image processing and object identification technologies, as well as the advent of various public data sources, have all contributed to the rapid growth of research into the localisation and classification of leaf diseases from crop pictures. Disease localization, the initial phase in the detection process, makes extensive use of distinctive data generated from models to identify outbreaks and determine the severity of illness. A fully linked CNN weed detection network, for instance, was utilised in [1] to locate and segment weeds in challenging situations. ResNet-50 network is used for autonomous diagnosis of leaf illnesses, In [2] the authors expanded the dataset's diversity by haphazardly incorporating backdrop from the ILSVRC15 database into leaf images. In order to create a two-stage variable universe fusion network detection and classification approach, according to [3] 95.71% of the detections made using YOLOv3's quick detection capability were accurate.

## III. DATASET

Gathering the required photos and creating the dataset on our own, or by choosing appropriate existing datasets for the purpose, is the first and most crucial step in training a deep learning model. A dataset of labelled images is used to develop, test, and evaluate a neural network model's performance. It is believed that convolutional neural networks can learn from the images in the dataset. The dataset is image-processed before being input into the training module, which is constantly monitored for training accuracy and loss at each epoch . The dataset used for training the model is made up of 2321 RGB images of different plant leaf diseases gathered from the Kaggle website. Fig 1 displays a few of the dataset's photos



Fig.1. Some random images of Dataset

## IV. PROPOSED METHOD

Identifying the plant leaf diseases at the earliest is crucial. It is important to survey the area and classify leaf diseases. One such approach is object detection, and the One of the top object detection models is the yolo model. By supplying class probabilities and utilising convolutional neural networks, A real-time object recognition system called Yolo (You Only Look Once) was created by Joseph Redmon and colleagues[5].

It went through revisions after that and the latest Yolo version is Yolov8. For YOLO prediction, one CNN propagation pass is sufficient. Yolo is one such object detection model that performs both detection and classification. Therefore, in the proposed system that solves the food safety problem by identifying different plant leaf diseases, we compared different versions of the YOLOv5 and YOLOv8 models.

### 4.1 Model for identifying and classifying plant leaf diseases

Against the PASCAL VOC tracking dataset, Yolo is created using convolutional neural networks and evaluated [4]. The fully connected layers of the network anticipate the probability and coordinates of the output, while the network's first convolutional layers harvest visual information. The YOLO network's architecture draws influence from the GoogLeNet image classification system. There are 24 layers of folds in the web, followed by 2 completely joined layers. It simply employs 11 reduction stages followed by 33 convolution stages in place of the initial GoogLeNet modules. A network is displayed in Fig. 2

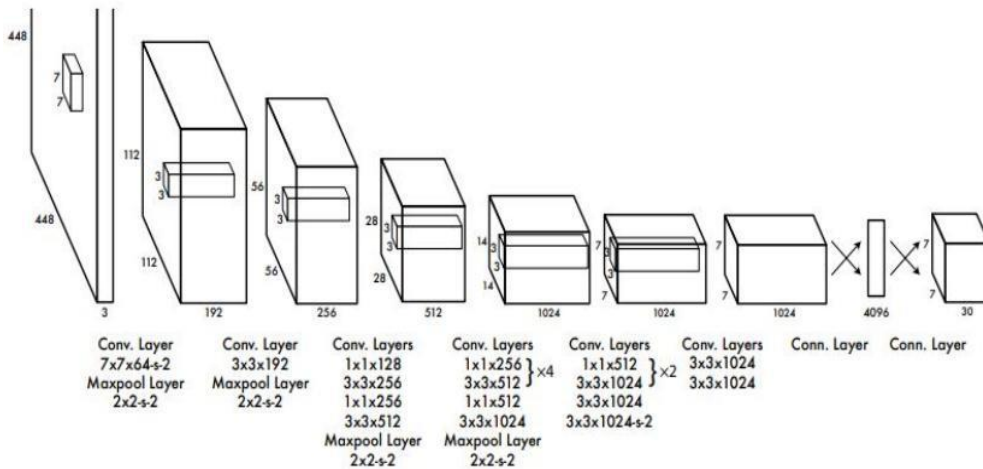


Fig.2 : Yolo network architecture

### 4.2 YOLOv5 model architecture

CSP-Darknet53 serves as the backbone of YOLOv5. Simply put, CSP-Darknet53 is YOLOv3's backbone, which is a Darknet53 convolutional network to which the authors incorporated the Cross Stage Partial (CSP) network technique. There were two significant neck adjustments performed by YOLOv5. Prior to adding BottleNeckCSP to the Path Aggregation Network (PANet) design, a type of Spatial Pyramid Pooling (SPP) was used. In YOLOv4's predecessor, PANet, a pyramid network of functions was employed to streamline information flow and make it easier for pixels to be placed correctly during the mask prediction process. The output from the PP block, which combines the data from the inputs, is fixed in length. Because of this, it has the advantage of significantly increasing the receptive area and splitting the most important context-relevant elements without slowing down the network.

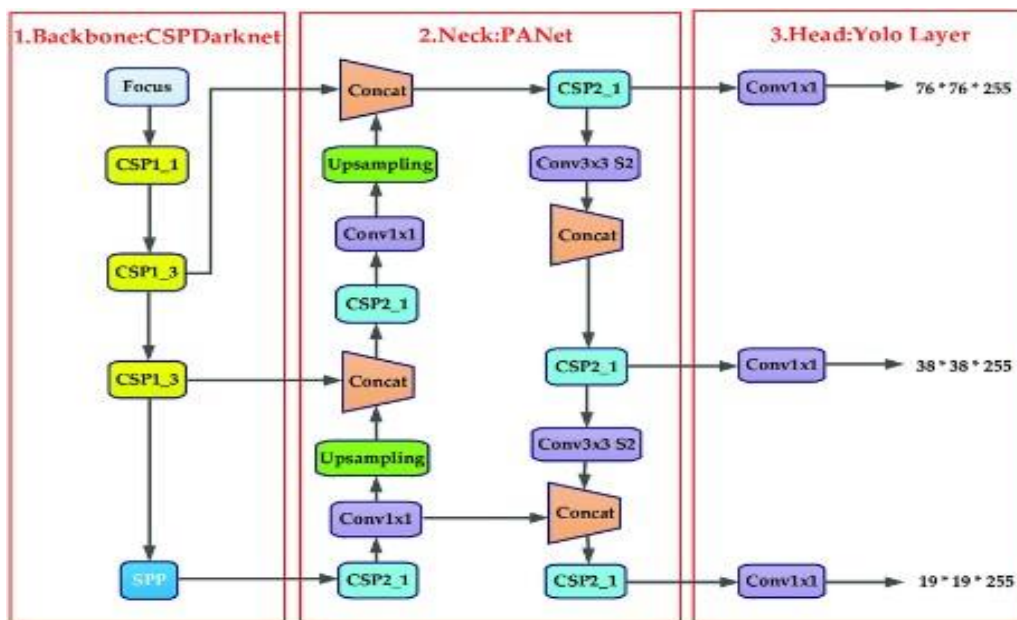


Fig.3: Yolov5 network architecture

### 4.3 YOLOv8 model architecture

YOLOv8 acts as object detection and image segmentation model. YOLOv8 is a state-of-the-art model (SOTA) that builds on the success of previous versions of YOLO, introducing new features and improvements to further increase performance and flexibility. One of the main features of YOLOv8 is its extensibility. This makes YOLOv8 the perfect choice for users who want to use the latest YOLO technology while using existing YOLO models.

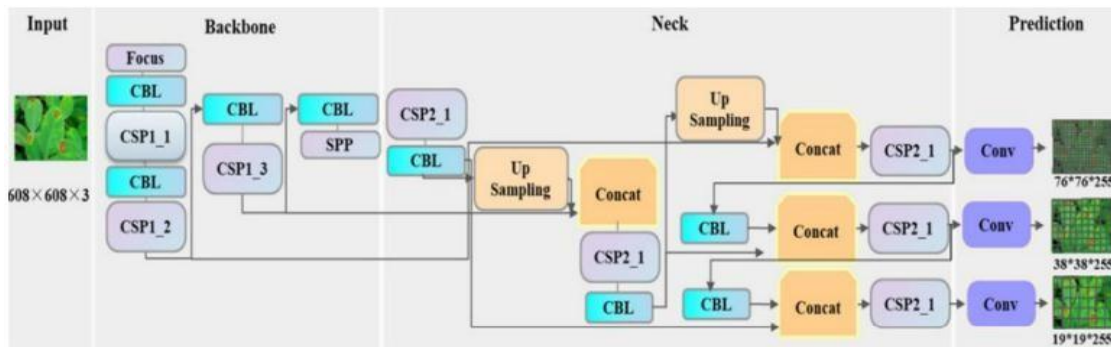


Fig.4: The complete architecture of YOLO model used in identification and classification of plant diseases with backbone, neck and prediction layer.

V. TRAINING AND EVALUATION

The training set, validation set, and test set of the study's dataset are split in an 8:1:1 ratio. For testing and training, the various network models YOLOv5, YOLOv8, and others are chosen. The optimizer employed SGD with a learner progress of 0.0001.

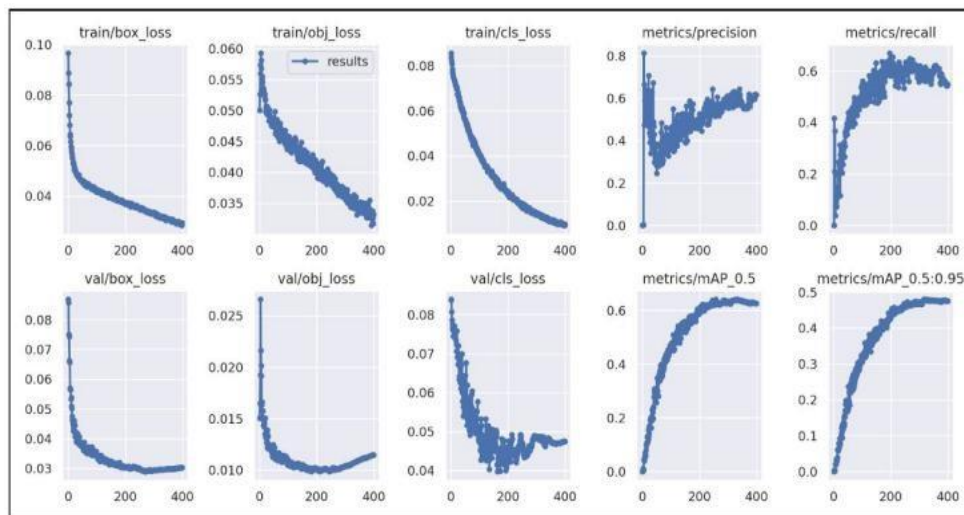


Fig.5: Model evaluation training indicators

5.1 Testing Results:

Sample results for YOLOv5 model and YOLOv8 model are presented in Figure 7 and 8.



Fig.7 : Sample testing results of YOLOv5 model



Fig.8: Sample testing results of YOLOv8 model



## VI. RESULTS AND DISCUSSION

The quantity of true positives determines precision (i.e., correctly identified objects) divided by the total number of favourable detections (both genuine and fake favourable results). It measures how precise the model is in identifying objects, i.e., the percentage of objects it identifies that are actually correct. As opposed to this, recall is determined as the sum of the true positives and the ground truth objects (both true positives and false negatives). It measures how many of the actual objects in the scene were correctly detected by the model, i.e., the proportion of objects it identified among all the objects that should have been identified. In object detection, these metrics are used to assess the model's performance on a dataset of tagged photos, where the real world data images limiting boxes for objects are known. Calculations are made by comparing the real world limiting boxes with the model's output bounding boxes with precision, recall, and mAP. Generally, for an object detection model mAP(mean average precision) greater than 0.5 is considered as the best model. So, both the models trained for disease classification on YOLOv5 and YOLOv8 are considered best models, but comparatively, YOLOv5 outperformed for the disease identification task. The dataset and balance of a particular model both have an impact on how accurate it is. YOLOv5 is the best model for the dataset under consideration, and it can yield better results by being optimised.

Table1: Results of YOLOv5 and YOLOv8

Model	Precision	Recall	mAP
YOLOv5	0.96	0.91	0.63
YOLOv8	0.97	0.94	0.52

## VII. CONCLUSION

The crops and plants are an important part of agriculture and they need to be protected. This requires a thorough knowledge of the type of plants being grown and the possible diseases that the plants may suffer from. In order to accomplish the intended outcomes, we developed an automated illness detection model in our study that employs image processing methods as amplification, segmentation, feature extraction, and classification. Using the YOLO network to detect whether a leaf of a plant is affected or not was found to have a higher accuracy rate. These techniques help farmers detect diseases at an early stage so they can control and warn against them. In order for every farmer to profit from this approach, the study's scope will be broadened in the future to include more diseases that are being classified.

## REFERENCES

- [1]. Wu, N., Weng, S., Chen, J., Xiao, Q., Zhang, C., and He, Y.: Deep convolution neural network with weighted loss to detect rice seeds vigor based on hyper spectral imaging under the sample-imbalanced condition. *Computers and Electronics in Agriculture*. Vol. 196. (2022).
- [2]. Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., Johannes.: A Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. *Computers and Electronics in Agriculture*. Vol. 161 (2018).
- [3]. Xu, W., Zhao, L., Li, J., Shang, S., Ding, X., Wang, T.: Detection and classification of tea buds based on deep learning. *Computers and Electronics in Agriculture*. Vol. 192, (2022).
- [4]. M. Everingham, S. M. A. Eslami, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman.: The pascal visual object classes challenge: A retrospective. *International Journal of Computer Vision*. Vol. 111(1), PP. 98–136. (2015)
- [5]. Redmon, J., Divvala, S., Girshick, R., and Farhadi. "You Only Look Once: Unified, Real-Time Object Detection", *IEEE Computer Vision and Pattern Recognition Conference Proceedings*, PP. 779-788, (2016).
- [6]. Santos. T. T, deSouza. L. L, dosSantos. A. A., Avila. S.: Grape detection, segmentation, and tracking using deep neural networks and three-dimensional association. . *Computers and Electronics in Agriculture*. Vol. 170 (2020).
- [7]. Haiqing Wang, Shuqi Shang, Dongwei Wang, Xiaoning He, Kai Feng, and Hao Zhu.: The Plant Disease Detection and Classification Approach Based on the Optimized Lightweight YOLOv5 Model. *Agriculture*. Vol. 12(7), (2022.)