Journal of Theoretical and Applied Information Technology
15th March 2025. Vol.103. No.5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

NOVEL PERFORMANCE ANALYSIS OF YOLOV5 AND YOLOV8 FOR CURCUMA LONGA LEAF DISEASE IDENTIFICATION

RANJITHKUMAR BANALA[1] and RAJESH DUVVURU[2*]

[1,2] School of Computer Science and Engineering, VIT-AP University, Amaravati, India.

Email: [1]ranjith.22phd7037@vitap.ac.in,[2]dr.rajeshduvvuru@gmail.com
Corresponding author Email: dr.rajeshduvvuru@gmail.com

ABSTRACT

The medical plant leaf disease detection plays a crucial role in the production of high-quality medicines globally. Particularly, the medicinal leaves used in Ayurveda medicine have significantly reduced the impact of COVID-19 in India and other parts of the world. Among such medicinal plants, the Curcuma longa, popularly known as turmeric, acts as an antibiotic that reduces the impact of lung-infected diseases. The current study concentrates on identifying early diseases in Curcuma longa leaves to enhance production, a significant challenge for farmers and practitioners. The current study pinpoints the most effective deep learning algorithms for distinguishing between the three classes of Curcuma longa: healthy leaves, leaf blotch, and leaf spot. The study employed the most popular and successful deep learning methods, such as Yolo V5 and V8, to identify the diseases for the first time on the 'Duggirala variant Curcuma longa Dataset', and achieved very high classification results. The mean average precision (mAP) results of YoloV5 have achieved 98.6%, whereas the YoloV8 method attained only 86.1%. We base the performance metrics of the two algorithms on training loss and validation loss, characterizing both training and validation losses with parameters like objectness (85%), box validation (96%), and classification analysis (98.2%). Based on our experimentation, we found that YoloV8 exhibits very high training loss and validation loss, while YoloV5 shows minimal losses. The experimentation results state that YoloV5 is best suited to detect the diseased and healthy classes for the novel Duggirala variant Curcuma longa Dataset. Overall, Yolov5 outperforms YoloV8 by 12.8 percent, and we recommend using the YoloV5 model for smart farming in turmeric plantations over other deep-learning models.

Keywords: *Deep Learning, Image Processing, Yolov5, Yolov8, Curcuma Longa Leaf Diseases.*

1. INTRODUCTION

Early leaf disease detection in medicinal plants plays a crucial role in the higher production of medicines at affordable prices, and it serves best in achieving the Third Sustainable Development Goal (SDG) of the United Nations (UN). The SDG-3 states that "Good Health and Wellbeing" aims to ensure that eight billion people worldwide need medication and vaccines for their health and sustainability. In particular, the COVID-19 pandemic has caused a global crisis, with the WHO COVID-2024 report recording 265k deaths worldwide [1]. The primary symptoms of COVID-19 include high fever, severe coughing, respiratory illness, exhaustion, and loss of taste or odor, among others [2]. The Ayurveda treatment played an important role on par with allopathic medication in treating COVID-19 patients [3]. In addition, the usage of allopathic treatment-based high-power steroids caused severe side effects to the lungs of COVID-19 patients through black fungus infections. Moreover, a few more patients experienced cardiac arrest as a result of steroid overdose. On the other side, Ayurveda medicine was crucial in treating COVID-19 patients without effects. Most of the COVID-19 Ayurveda medicine species comprise *Ashwagandha (Withaniasomnifera), Tulsi (Holy Basil), Turmeric (Curcuma longa), Giloy (Tinospora cordifolia), Mulethi (Licorice Root), Ayurveda Breathing Practices (Pranayama), and Amalaki (Indian Gooseberry)* [4]. Turmeric, in particular, plays a crucial role in eliminating bacteria due to its potent antioxidant and anti-inflammatory properties. Many people use yellow milk (turmeric milk) with

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

black pepper to strengthen their immune systems and aid in the healing of respiratory ailments [5-7]. With around 80% of the world's supply of turmeric, India is the biggest producer and exporter of turmeric [8]. Turmeric is one of the major crops in Indian agriculture; it is known for its vivid yellow color and potent medicinal qualities [9]. The state of Telangana, Andhra Pradesh, Tamil Nadu, Odisha, Karnataka, and Maharashtra are among the main growing areas. Unfavorable weather and diseases caused by the turmeric crop are likely to significantly reduce India's turmeric production. Extended dry spells during the growing season, especially in key states like Tamil Nadu, Telangana, and Andhra Pradesh, have led to an anticipated drop in output of around 20%–30%. Diseases such as leaf blotch, leaf spot, and leaf blight can influence crop productivity. Identifying suitable identification and prevention methods is crucial to boost the production rate. The implementation of early disease detection and control strategies is likely to reduce pesticide usage and enhance environmental sustainability. Traditional approaches for detecting leaf diseases often fail to yield higher crop production. Machine learning and deep learning technologies offer significant benefits compared to traditional recognition techniques and manual diagnostic processes [10].

These diseases are becoming more prevalent as a result of climate action, which has a significant impact on the economy and poses a major challenge to a country's GDP. India, being an agriculture-based country, relies heavily on this sector for the livelihood of approximately 70% of its population. The agricultural industry contributes 4% to the global GDP and can represent up to 25% of the GDP in certain least developed nations. The dependent variable is the agricultural GDP, whereas the independent variables are the use of HYV seeds, pesticides, fertilizers, net irrigated areas, power, and rainfall [11]. The disease usually targets the leaves of the plant, but this new kind of illness mainly affects the roots, making them wither and preventing the plant from producing the healthy mother rhizome. Chemical treatments are ineffective in controlling this illness, but researchers are developing novel farming techniques. The present study focuses on the early disease detection of major herb crops such as turmeric plants. The turmeric diseases, like leaf spot and leaf blight, are the major ones. Improper detection of these diseases at an early stage is creating a greater loss for the farmers, and those infected crops are not used for the preparation of Ayurveda medicine.To improve the medical plant's growth and the quality of medicinal preparation, diseased leaf identification is one such pre-harvesting process, which is required on a large scale. The manual process will be longer to identify the crop's status. This work is distinctive since it represents the inaugural collection and analysis of a novel Duggirala turmeric dataset from fields for disease identification. Deep learning algorithms like YOLOV5 and YOLOV8 have not yet implemented an automation process for the early identification of turmeric sickness in Duggirala variants.

In recent times the digital technology has a substantial impact on agricultural operations, especially on tasks related to pre-harvesting and post-harvesting [12]. The early disease identification at a large scale is a challenging task for the farmers; especially, it is most critical in medicinal plants. The existing literature focused on disease detection of medicinal plants using multi-swarm coyote optimization (MSCO), improved Chan-Vese snake optimization (ICVSO), fitness-distance balance deep neural network (FDB-DNN), and modified logistic regression (MLR) on various herb OMICS datasets in understanding herbs and their features [24]. The disease detection algorithms are improving the classification accuracy from research to research by adding new data items into the dataset. Even an efficient classification accuracy is not achieved on the herbal plant disease detection due to the vast data availability of medicinal plants on earth. The dataset is not standardized so far. The present herbal dataset classification achieved by the turmeric dataset is 98% of herbs using only Support Vector Machine (SVM), Naive Bayes NB, and PNN [26]. Though many researchers carried out their research in detecting the turmeric diseases using various deep learning techniques, the detection accuracy is still limited. Especially the detection of Duggirala variant turmeric leaf disease detection is not so far. The current study goes into great detail about finding the best deep learning method to spot the sick leaves on the Duggirala turmeric variety. The current study focused on the early disease identification on turmeric leaf (Duggirala variant). The Duggirala turmeric is the most popular and richly used for the preparation of Ayurveda medicines. The Indian state of Andhra Pradesh is home to the Duggirala turmeric varietal. The Duggirala turmeric variant is lengthy, stocky fingers are distinctive for being sturdy, smooth, and long. There are 3% curcumin, diferuloylmethane, and Curcuma xanthorrhiza oil in the Duggirala Turmeric variant. Curcumin is a bioactive compound. Curcumin, the primary component of turmeric, serves as an indicator of quality, with elevated levels signifying superior quality. Lakadong turmeric is known for its high curcumin content, which is approximately 9%. This molecule demonstrates significant antimicrobial, pleiotropic, antioxidant, anti-inflammatory, hypoglycemic, wound-healing, and antibacterial properties.

The present study considered the Duggirala variant *Curcuma longa* leaf disease dataset, which is novel dataset that comprises of three kinds of leaf disease: leaf Bloch, leaf blight, and leaf spot. Currently, there is a need to advance intelligent artificial intelligence solutions that can effectively notify farmers and the agricultural department to prompt rapid reaction activities upon disease discovery. Identifying illnesses that affect the Curcuma longa (turmeric) crop is a considerable problem, especially in the early stages. The accuracy of identifying diseases early in Curcuma longa leaves is an important issue to the researchers since enhanced detection accuracies are largely contingent upon the training accuracy of the object. Nonetheless, researchers have performed restricted pre-training investigations to evaluate the efficacy of quick leaf disease identification. Typically, high training accuracy may lead to superior test accuracy. Although the neural network training model is renowned for its efficacy in object detection within images, the optimal epoch rate for data training remains undetermined. This study aims to integrate deep learning technologies for the identification and monitoring of disease attacks on the Curcuma longa plant crops, where the precision in the identification of multi-class illness leaf objects is inadequate. Object identification accuracy mostly relies on training precision; yet, researchers often lack clarity on how to configure hyperparameters, including epochs and optimizers, to get 100% accuracy. The accuracy of object detection is contingent upon the quality of training. Researchers often encounter difficulties in optimizing hyperparameters such as epochs and optimizers to achieve optimal accuracy. The selection of the training network is contingent upon data attributes and the quantity of classes, with the objective of maximizing accuracy. The present study used two prominent deep learning models, YOLOv5 and YOLOv8, for enhanced training precision on a newly developed custom dataset of Curcuma longa leaves. We gathered 8,142 photos of diseased and healthy *Curcuma longa* leaves from diverse locations of Andhra Pradesh with no segmentation for this study. We execute each training network independently, maintaining uniformity in all other hyperparameters (such as epoch, optimizer, etc.). We transition between epochs at an interval difference of 10 each. An analysis of Yolov5 and Yolov8 reveals that Yolov5 outperformed Yolov8 in some epochs, achieving a training classification accuracy of 98.6%. In every era, the achievement rate of Yolov5 surpasses that of Yolov8. The Yolov5 deep-learning model has accuracy in training of 98.6% when the classes are restricted and less intricate. When trained on datasets of Curcuma longa leaves including photos of both diseased and healthy specimens, the YOLOv5 and YOLOv8 deep-learning models achieve accuracy rates ranging from 23% to 50%, with further assistance. In order to increase training accuracy, the present research determined the optimal deep learning training model, epoch, and optimizer rates for balance Curcuma longa illness and health leaf datasets. While little study has been done on Curcuma longa leaves data, the current work is confined to confirming the greatest training accuracy on well-known deep learning models, especially YOLOv5 and YOLOv8. Using Curcuma longa datasets, this study seeks to determine the ideal hyperparameters to achieve greater accuracies on YOLOv5 and YOLOv8. Based on the training results analysis of the dataset, Yolov5 seems to be the best network for using detection techniques. Only training issues using Curcuma longa leaves datasets are the subject of the present study, and it also has to be tested for accuracy using detector algorithms like YOLO, CenterNet, etc. The current work found that the existing Yolov5 model is superior for training on the Curcuma longa leaf dataset when it includes photos of both diseased and healthy specimens. This technical examination is advantageous to the Formers, who now possess inadequate resources for managing damaged rhizomes in the crop. Establishing a system for the periodic dissemination of Geographical Data and Early Warnings will facilitate the early diagnosis of plant diseases, possibly mitigating economic and production losses.

Contributions:

- This work has introduced a novel Duggirala variant turmeric leaf plant dataset. The dataset includes 8,142 leaf images, further classified into three distinct classes: healthy, leaf blotch and leaf spot.
- This study used YOLO V5 and YOLO V8 to show a new way to look at a dataset of new Duggirala variant turmeric leaf plants to find diseases early on.
- We used YOLOV5 to get a classification accuracy of 98.6% when looking at the new turmeric dataset to find diseased leaves. This study suggests using YOLOV5-based DarkNet to find leaves that are sick in the new Duggirala variant turmeric leaf plant dataset. Even though the YOLOv8 is a recent release, the YOLOv5 performance is still dominant in achieving higher classification accuracy.

We structure the remainder of the paper as follows: Section II comprises the literature review, Section III delineates the study area. Section IV addresses the dataset; Section V delves into the design of the YOLO model. Section VI presents the mathematical notations and formulas, while Section VII Describes the Yolo model's results. Section VIII presents the Discussion of Yolo5 and Yolo8. Section IX is a summary of the complete work.

2. LITERATURE REVIEW

We looked at the literature that is being used for the classification and identification of diseases in plants and conducted a critical assessment of training and testing the Leaf data. Researchers work on classifying plant diseases can be broken down into two groups: ML-based methods and DL-based approaches.

Using both private and publicly accessible datasets, ascertain the optimal hyperparameters for the categorization and identification of diseased and healthy leaf sections. The YOLO v5 model performed well in the test dataset, with an accuracy rate of 93%. Rajamohanan, R. and Latha et.al., [13] A system for detecting and classifying cotton plants, with or without abnormalities, was developed. A network must be pragmatic, viable, and reliable to provide frequent monitoring of cotton plants and prompt diagnosis. Due to its effectiveness in object identification, deep learning was integrated into the system by amalgamating a version of yolov3 with neural network methodologies. The selected model achieved a mean Average Precision (mAP) score of 95.09%, indicating substantial performance. Susa, J.A.B. et.al.,[14] Pest affects most of the crop damage in a short period to resolve existing issues in pest identification, therefore aligning current methodologies with the increasing demands of agriculture, especially crops such as rice and maize. Yolov5, the methodology used for identifying the pest in the crop, is better than the existing work in terms of accuracy by Dong, Qing, et al. [15] Artificial neural network architectures that exhibit a high degree of accuracy use GPUs with substantial processing capabilities, hence augmenting the total system size. Processing Machine Learning algorithms to address this issue is not economically viable; instead, they developed smart classes for recognizing unhealthy leaves. Ponnusamy, V., .et.al., [16] The YOLOv7 algorithm is utilized to detect and diagnose several forms of tea leaf diseases in tea gardens. The suggested approach autonomously identified five separate categories of tea leaf illnesses and distinguished between healthy and infected leaves and achieved an accuracy of 97 % by Soeb, Md Janibul Alam, et al [17] The cause to decline in crop quality and quantity is a lack of knowledge among farmers worldwide regarding rice leaf disease, which makes it difficult for them to diagnose the condition accurately. The YOLO V5 is a far more accurate method than previous ones (SVM, VGG16 & ResNet V2). Haque, M.E., et.al [18] The author classified the data by using Sense software and created the private dataset used for the analysis, after choosing clear, moderately sized images of apple leaves from Baidu Paddle, Paddle's image collection to identify different apple leaf illnesses. The model's mAP@0.5 value is 95.9%, higher than YOLOv4, SSD, Faster RCNN, and YOLOv5, by 9.4%, 14.7%, 5.6%, and 6.1%, respectively. Apple-Net scored 93.1% on the accuracy indicator, which is almost 5.5% higher than YOLOv5.Zhu, R., Zou.et.al [19] A leaf spot is a small, discolored, diseased area on a leaf caused by plant infections caused by bacteria, viruses, or parasites, as well as wounds from nematodes, insects, environmental factors, hazardous substances, or herbicides. There is often a focal focus of putrefaction or cell death in these discolored patches or lesions. While symptoms might differ between cause experts, the kind of leaf spot disease can be determined by looking at the signs and indicators of certain bacteria. Vanitha, C.N., et.al [20] The author employed a variety of machine-learning algorithms to enhance the accuracy of leaf disease detection. convolutional neural networks, Artificial neural networks, global pooling dilated generative adversarial Networks, Support Vector machines, convolutional neural networks, and particle swarm optimization techniques are used for training the leaves to detect diseases in the leaves. The global pooling dilated convolution neural networks show good accuracy compared with the other training algorithms. Raina, S. and Gupta et.al [21] From analyzing these photos, algorithms are trained to recognize subtle visual clues that suggest the existence of a disease. YoloV5 and YoloV8 algorithms are used in the field to quickly and accurately identify tomato illnesses once they have been trained. It is critical to identify an illness early on. Farmers may prevent the spread of illness and save their priceless harvests by promptly implementing targeted treatments or separating impacted plants Ahmed, R. et.al [22].

3. STUDY AREA

The study area Duggirala village of Kollipera mandal, covering 412 km, is situated inside the Guntur District (16°18'23.95" N and 80°26'11.54" E), as seen on the geographical map (Fig 1). The Guntur District's soil and climate are ideal for the development of Curcuma longa. Guntur District, one of the biggest Curcuma longa growers, is a significant center for this crop production. Furthermore, Guntur is home to one of India's largest Curcuma longa markets. The Guntur district, located in the Right Canal's command area of Nagarjuna Sagar, is primarily responsible for growing Curcuma longa. In 2023, production reached 73,000 metric tons, which accounts for more than 60% of the nation's total production. The Guntur District is renowned for producing excellent Curcuma longa. The research region produces Curcuma longa crops with higher-quality curcumin, but it is also very vulnerable to many disease outbreaks, which increase losses.

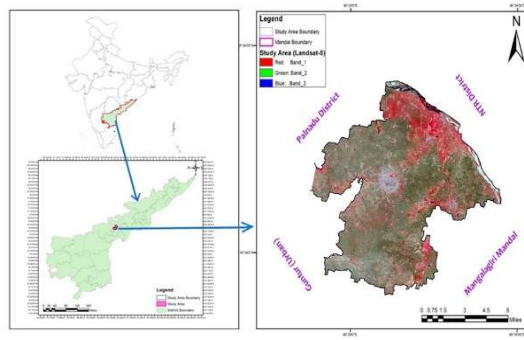
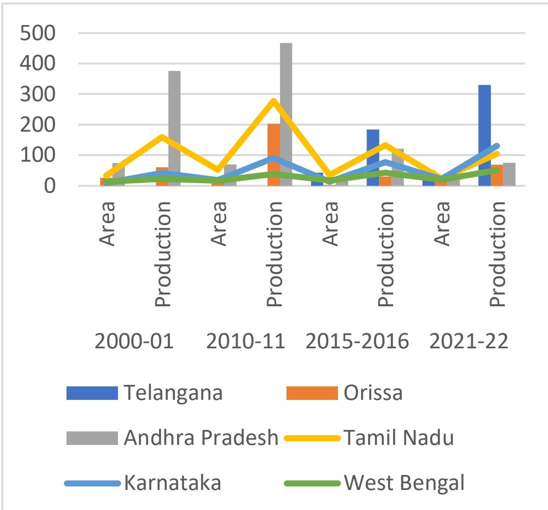


Figure1: Location map of the study area Earth Explorer (NASA Explore)

Turmeric is grown on 3.49 lakh hectares of land in India, and 13.34 lakh tons were produced there in 2021–2022. In India, the area planted to spices and condiments is around 7.77 percent; moreover, turmeric makes up 12.33 percent of the country's overall output of spices and condiments. In 2021–2022, Andhra Pradesh generates 0.75 lakh tonnes of turmeric from 0.26 lakh hectares, or 5.59% of the country's total production (Spices Board of India). Figure 2 illustrates the decadal analysis of turmeric production, area, and yield in India. Andhra Pradesh, Tamil Nadu, Telangana, Karnataka, and Odisha are the leading turmeric-producing states in India. Telangana accounts for 14.33% of India's total area dedicated to turmeric production, followed by Karnataka (6.10%), West Bengal (5.38%), Orissa (8.92%), Andhra Pradesh (7.32%), and Tamil Nadu (6.93%). Sangli (Maharashtra), Nizamabad (Telangana), Salem, Erode, Dharmapuri, and Coimbatore (Tamil Nadu), Duggirala (Andhra Pradesh) are the primary hubs for turmeric commerce in India. Disease and healthy pictures 2728 of three classifications connected to the Curcuma longa leaves comprise the dataset. Three categories make up the dataset: 70% is used for training, 10% is meant for testing, and 20% is put aside for validation. To identify diseases early, this research specifically focused on Curcuma longa pictures damaged by illness. Many different disease assaults, such as Leaf spot, Leaf blotch, Root Rhizome, etc., on the Curcuma longa dataset. However, among all the others, leaf spot and leaf Bloch are common diseases that severely harm Curcuma longa crops in the research region. This effort selected often disease-infected and healthy leaves for testing, such as Healthy leaves, Leafspot, and Leaf Bloch, in order to prevent significant losses to farmers. Three datasets affecting a broad range of Curcuma longa leaf varieties, including Duggirala and Kadapa variants,



are included in the current dataset.

Figure2: Major Curcuma longa producing states (Area-ha, Production-tonnes)

4. CURCUMALONGA DATASET

The researcher gathered from location area Duggirala village and an unprocessed dataset of Curcuma longa leaves from the field, including 743 photos categorized into three unique groups.

4.1. Dataset Pre-processing

• Data profiling: The raw Curcuma longa leaf dataset underwent profile steps that included investigation of size distribution, brightness, distribution, and shuffling. Curcuma longa leaf datasets are analyzed with the Roboflow program, with the focus on picture quality parameters such as aspect ratios, color distribution, brightness, convexity, fine details, resolution, and image segmentation.

• Data cleaning: We removed erroneous, corrupted, badly formatted, redundant, or incomplete photographs of Curcuma longa leaves from the collection. A total of 250 shots of Leaf Bloch were collected, and 20 images were excluded from the collection. In all, 248 Leaf spot photos were gathered, of which 19 were rejected; the majority were duplicates, with just a few being unclear. Curcuma longa Healthy Leaves has collected 245 pictures. However, we eliminated 22 of these photographs due to their inadequate quality and brightness. We exclude 61 odd data points from the original dataset of 743, yielding a remaining set of 682 photos to restore dataset balance.

• Balanced dataset: The categorization of balanced datasets results in superior accuracy and less bias relative to unbalanced datasets. For the present research, we compiled a collection of 682 high-quality pictures of Curcuma longa leaves. The photographs were then scaled to a size of 720 × 720 pixels for each category.

• Augmentation: Each picture of the Curcuma longa leaf undergoes augmentation, which includes auto-orient (90 degrees and 180 degrees), auto-adjust contrast (adaptive equalization), isolate objects (background clutter), and grayscale. This process yields a total of 2,728 enhanced photos. The dataset is divided into three segments: 70% for training, 20% for testing, and 10% for validation.

4.2. Leafspot (Colletotrichum capsici)

On leaves, there are oblong brown dots with gray centers. The dots are around 4-5 cm long and 2-3 cm wide. In more severe stages of the illness, concentric rings of black spots on the site reflect fungal activity. The gray cores split and become thin. Leaves with severe damage dry out and wilt. There are bright halos all around them. One leaf may have an infinite number of spots, and as the illness progresses, the spots become bigger and cover a significant amount of the leaf blade. Usually around October and November, lower leaves start to show symptoms of this illness. Most of the individual dots have a rectangular form. The disease is characterized by several spots appearing on both leaf surfaces, with the majority of the spots appearing on the top side. Figure3 shows the sample leaves with Leaf spot disease.

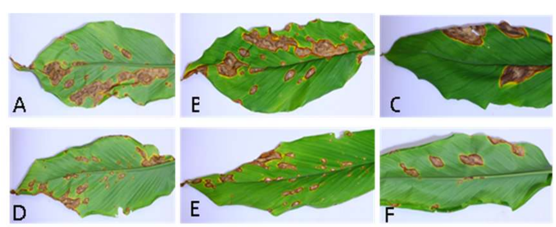


Figure 3: The sample diseased images dataset of Curcuma longa leaf spots(A-F).

4.2. Leaf Bloch

The ascomycetous fungus Taphrina macula's is the primary cause of leaf blotch, a serious foliar disease of turmeric. It may strike turmeric plants at any stage of development, and in vulnerable kinds, it can cost growers a substantial amount of money. The illness is most common in October and November when temperatures between 21 and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

23°C and relative humidity levels between 80 and 90% are ideal. Usually around October and November, lower leaves start to show symptoms of this illness. The individual spots are mostly oval and have a width of 1-2 mm. The disease is characterized by several spots appearing on both leaf surfaces, with the majority of the spots appearing on the top side. Rows of them are placed along the veins. The dots freely combine to generate asymmetrical lesions. They start as light yellow stains and eventually become a filthy yellow tone. The diseased leaves get discolored and look reddish-brown. Figure 4 shows the sample data leaves with Leaf Bloch disease.

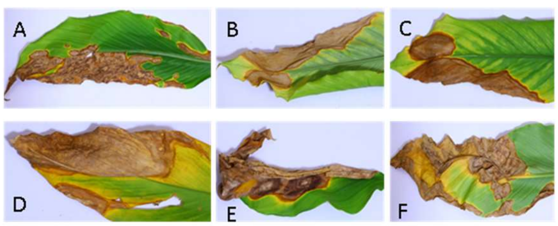


Figure 4: The sample diseased images dataset of Curcuma longa leaf blotch (A-F).

4.3 Healthy Leaves

Turmeric leaves have an average length of 80–115 centimeters and a width of 30-48 centimeters. They are small to medium in size and have an oblong or lanceolate form. The sturdy, upright green stem, which is attached to a golden root, gives rise to the smooth, light green leaves. Fresh turmeric leaves smell neutral, but when they are chopped, ground, or chewed, they create a unique acidic taste with grassy and minty overtones. Turmeric leaves have a flowery, spicy, gingery taste with hints of bitterness when cooked. While dried turmeric leaves are accessible all year round, fresh turmeric leaves are only available from spring through October. Sample healthy leaves in the dataset are shown in the figure5.

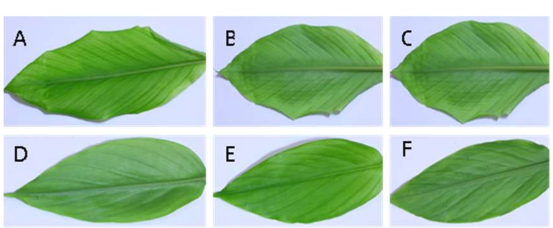


Figure 5: The sample Healthy images dataset of Curcuma longa (A-F).

5. METHODOLOGY

The proposed system method comprises six steps: data collection, preprocessing, leaf dataset training, testing, and a classification performance matrix. The method explains the step-by-step process of the classification of Curcuma longa. The dataset starts with three classes of leaf images: 645 Curcuma longa leaves dataset created and preprocess the dataset using auto-orient (90 degrees and 180 degrees), auto-adjust contrast (adaptive equalization), Random noise (reduce noise), and grayscale techniques. We then use CSP-DarkNet53 for the training backbone and PANet for the neck across different epochs. The two YOLO versions underwent testing, maintaining different parameters as constants. Finally, figure out how well the YOLOv5 and YOLOv8 classify Curcuma longa leaf disease with mPA = 0.5, epochs, training loss, and validation loss. Figure 6 shows the methodology of the proposed system for detecting Curcuma longa leaf disease classification.

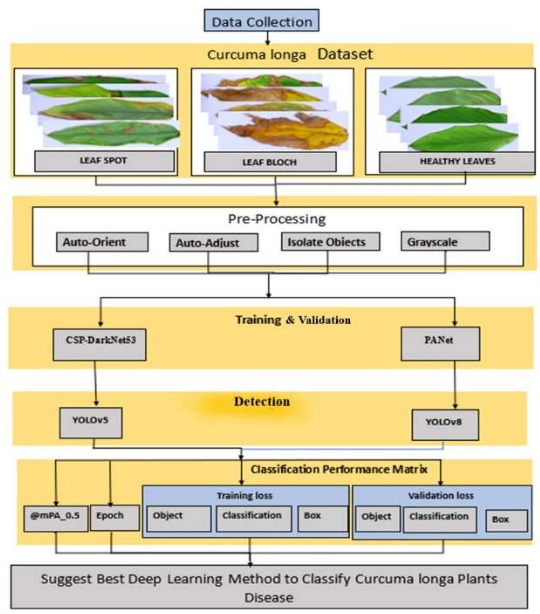


Figure 6: Proposed methodology of the Curcuma longa Leaf disease detection.

6. ARCHITECTURE

6.1. YOLOv5 model

The computer vision YOLOv5 model is a member of the YOLO family. YOLOv5 is used for object identification. It comes in four major varieties, small (s), large (l), medium (m), and extra-large (x) each having a distinct accuracy level. Object detection is the main use case for YOLOv5, which is the extraction of features from images. Classes and object boundaries are expected to be defined by

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

these features. The YOLOv5 model is composed of three elements: Backbone (CSP-Darknet-53): A CNN with several scales. (b) Neck (PANet): An arrangement of different layers that combines and enhances visual characteristics before predicting the object. (c) Head: Forecasts box and class based on neck features. Yolov5 Architecture with Backbone CSP darknet, Neck PaNet, and the head Yolo layers are shown in Figure7.

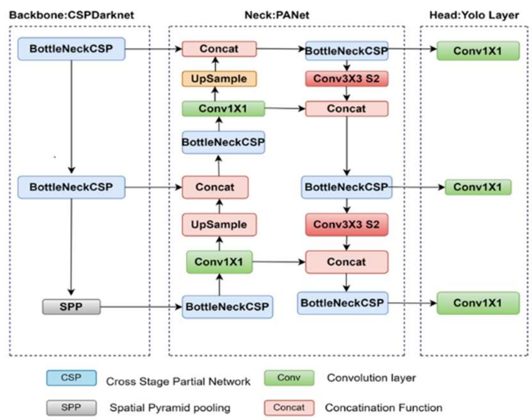


Figure7: Architecture of Yolov5 detector with Darknet as Back-bone network.

6.2 CSP-DarkNet53 Training Architecture

Darknet-53 uses a cutting-edge method called Cross Stage Partial Network (CSPNet) to improve DarkNet-53. CSP-DarkNet-53's divide-and-conquer approach enables the system to split the leaf disease and healthy leaf data into more manageable chunks for processing. Then, it merges these portions once again into a more comprehensive representation of the input Curcuma longa leaf data via cross-stage connections. Two convolution layers (1x1) are typically created from the provided input Curcuma longa leaf data using the CSP-DarkNet-53 training architecture. Part 2 has four convolution layers, three of which have 1x1 filter sizes and one of which has 3x3 filter sizes. Part 1 only has one convolution layer. Finally, the two components are combined into a single, 1x1 convolution layer, after which the output Diseased leaf and healthy leaf are categorized. Figure8 illustrates the architectural levels of Yolov5 CSP-Darknet-53 training.

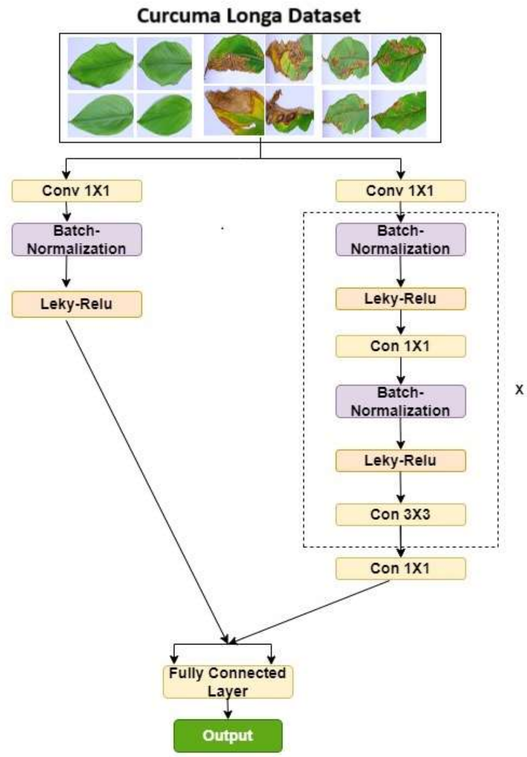


Figure 8: CSP-DarkNet-53 architecture Curcuma longa leaf data training of Backbone.

6.3 Training Architecture PANet (Neck)

Path Aggregation Network has three training phases to enhance performance. A bottom-up approach is adjusted to enhance the dissemination of low-level information. We create adaptive feature pooling to enable each identification to use data from every level for the prediction of categorized leaves. The Bottom-up Path Augmentation method yields less than 10 layers at these levels. The CNN stem in the FPN traverses about a hundred levels, beginning from low to high. Enhanced Bottom-Up Framework: Factor 2 reduces the spatial dimensions from P2 to P5. Apply {N2, N3, N4, N5} to represent newly created disease and healthy features. Adaptive Feature Pooling: It assigns small concepts to subordinate feature levels and significant ones to superior levels. While straightforward and efficient, it may provide suboptimal Categorized leaf data. Completely connected fusion (FC layers) contrasts with Fully Convolutional Networks (FCN), which forecast every single pixel with an individual responsive area and share parameters across many spatial regions. Conversely, fully connected layers are location-sensitive as they use distinct parameters to predict different geographical areas of diseased leaves. This allows for adaptation to many spatial situations, as shown in Figure 9.

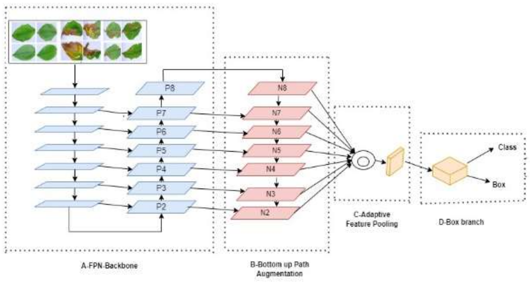


Figure 9: PANet architecture for training Neck of Curcuma longa classes (Healthy Leaf, Leaf Spot, and Leaf Bloch).

6.4 Detector: You Only Look Once -Version8

The YOLOv8 model is the most current addition to the YOLO model line. Object detectors within the YOLO framework operate in a single step. A backbone is used to extract Curcuma longa leaf characteristics from YOLO model picture frames. The neck is where the Curcuma longa characteristics are merged and integrated before being delivered to the network's head. YOLO predicts the location of bounding boxes and object types. During post-processing, YOLO applies non-maximum suppression (NMS) to produce its Disease and healthy leaf prediction. The developers of YOLOv8 build upon prior studies about how far a gradient must traverse for back-propagation with in the layers and space utilized for layer storage. Their neural network develops more efficiently if its gradient is reduced. The ultimate layer analysis used Extremely Effective Layer Aggregation, an augmented variation of the ELAN computing blocks, with the YOLOv8 architecture to identify the Disease class, as seen in Figure 10. It depicts the first three stages of the Yolov8 Curcuma longa leaf training procedure shown in Figure10.

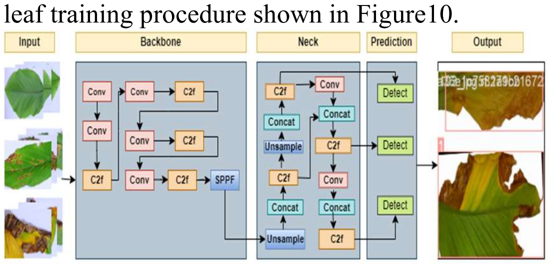


Figure 10: Architecture of YoloV8 to detect Curcuma longa leaf disease and healthy dataset.

7. MATHEMATICAL NOTATIONS

In YOLOv8, DFL was employed for bounding box regression, whereas YOLOv6 implemented VFL for the classification task. Understanding these loss functions provides clarity on the design choices and common obstacles faced in object detection as it aims to achieve both efficiency and accuracy in its outcomes.

$$\boldsymbol{\delta_s}(m) = \frac{1}{|s|\sqrt{\pi}} e^{-\left(\frac{m}{s}\right)^2} \quad (1)$$

Where δ is the distribution of unit impulse the value of this function is zero, s is the impulse value and m is the sample.

Distributed Focal Loss:

The regression goal is defined as the relative offset from the bounding box coordinates. The regression label k corresponds to the Dirac delta distribution, satisfying

$$\int_{-\infty}^{+\infty} \delta(P-k)dx = 1 \ (2)$$

The following is the integral form that is used to retrieve y.

$$m{=}\int_{-\infty}^{+\infty} \delta(p-k)\, p dx \qquad (3)$$

Now, given the range of label y with minimum K0 and maximum Kn, we estimate the value of Km.

This approach makes it possible to create a more versatile model that is not constrained by certain assumptions, such as those of Gaussian or Dirac delta distributions, and may conform to any shape of distribution. By specifically raising the probability value, the loss function promotes the value close to the label P and Pi.

$$DFL(s_{i,}s_{i+1} = (m - m_i)\log(s_{i+1})) \\ - ((m_{i+1} - m)\log(s_i) \quad (4)$$

It is expressed as a weighted sum of Pi. By altering the range from m0, mn to a collection of regularly spaced intervals m0, m1, m2, …, mn-1, mn, we may transform the integral in a continuous domain into a discrete representation. One way to display the estimated regression value is as follows:

$$\widehat{m} = \sum_{i=0}^{n} P(m_i)m_i \qquad (5)$$

The loss function pushes the number closer to the label m by making it more likely that mi and mi+1 will happen. when the above equation is observed, it shows a weighted sum of mi.

8. RESULTS

In general, the deep learning model results in statistics areas majorly focused on training loss and validation loss. The diseased leaf identification results obtained from the experiment are presented and discussed as follows. The Curcuma longa leaf disease identification results statics were presented by considering five classification performance metrics Coordinate Loss, objectness, classification, accuracy, and recall which are often used to calculate the performance evaluation of diseased leaf recognition from multi-class Curcuma longa leaf image data.

8.1. Disease Detection using Yolov5

The YOLOv5 method for Curcuma longa leaf disease detection has achieved significant classification accuracy for the Curcuma longa dataset, specifically for healthy leaves (99.5%), leaf blotches (98.8%), and leaf spots (97.5%). All three classes of Curcuma longa leaf datasets yielded a mean accuracy precision (mAP) of 98.6%. Figure 11 displays the detailed gain and loss graphs using Precision and Recall (PR), and Figure 14 (A-B) shows the ROC curves that show the very high F1 score of 95.1% at 0.2.

8.1.1. Training Loss

The training loss is a statistic that measures how well the model's predictions match the ground truth leaf disease in the context of Curcuma longa leaf training for the YOLOv5 (You Only Look Once version 5) object identification model. The loss function of YOLOv5 consists of a number of parts that each focus on a distinct facet of the object identification problem. Training loss uses the objectness, box validation, and classification for detecting the diseased leaf with a loss function.

a. Objectness

Objectness loss quantifies the probability that an object will be found in a RoI to measure. With the Curcuma longa dataset, the training loss of the objectness is 0.017245, it is very small and regarded as a better spot indicating the presence of an object in the picture frame.

b. Box validation

The Curcuma longa disease class item is marked with the anticipated bounding box and obtained 0.026473 as training accuracy for classification, this is given in the box loss, it evaluates the model's efficacy in identifying the essential characteristics of the sickness in the leaf.

c. Classification

The algorithm's ability to anticipate and detect leaf disease on a leaf class is measured by classification loss. With a relatively higher classification accuracy for the low value, the loss function training value is 0.007152. The prediction model correctly predicted the diseased leaf class, as seen by the Precision value of 0.871059. The Yolo5 model effectively located every item in the targeted leaf Disease class, as shown by the recall value of 0.810257. The extremely excellent categorization is shown by the mAP of 0.849624. The labelling of the Curcuma longa leaf during the training process is shown in Figure 11.

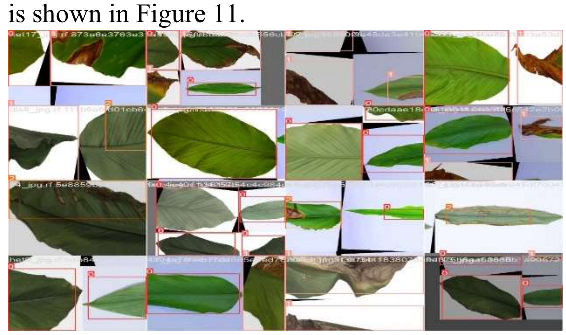


Figure 11: Class labelling of Curcuma longa Leaf during training (PAN.ET).

8.1.2. Validation Loss

The effectiveness of a deep learning model on the validation set is assessed using a metric known as validation loss. The validation set is a portion of the dataset that has been set aside expressly for confirming the model's functionality. The validation loss is similar to the training loss as it is determined by adding up all of the errors for each sample in the validation set. The leaf disease class confusion matrix and the peak performance metrics for YOLOv5's leaf disease Classification at 250 epochs are shown in Figures 11 and 12. Figure 12 displays a snapshot of the findings for the YOLOv5-identified disease leaf, and Figure 13 shows the PR curve and F1-score used to indicate the Curcuma longa leaf classification peak performance for YOLOv5.

a. Classification

The metric for the algorithm's predictive accuracy about a disease item inside a leaf class is termed classification loss. The loss rate of the training

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

classification value is 0.006752, indicating a minimal value that resulted in elevated classification accuracy. The precision rating of 0.780379 indicates that the prediction model accurately predicts the Disease class that is the focus. With a recall score of 0.804229, the Yolo5 model performed well in locating every item in the class of targeted leaf disease. The mean Average Precision (mAP) of 98.6%, the categorization is quite accurate (Figure. 14(A)).

b. Objectness

Objectness loss quantifies the probability of an item to exist inside a region of interest (RoI) of interest. With the Curcuma longa leaf dataset, the training loss of objectness is 0.009741, which is very small and regarded as a good match indicating the presence of an object in the picture frame (Fig 12).

c. Box Validation

The validation of box loss is whether the projected bounding box covers the Curcuma longa leaf class object, the model identifies the exact location of a diseased spot in the leaf and the classification training accuracy is 0.033569 (Fig. 13).

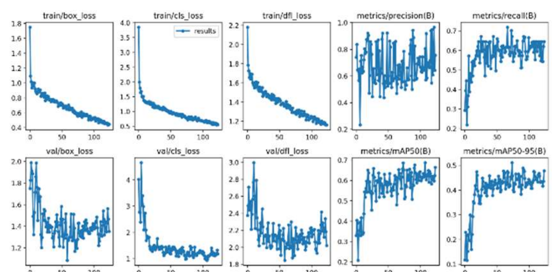
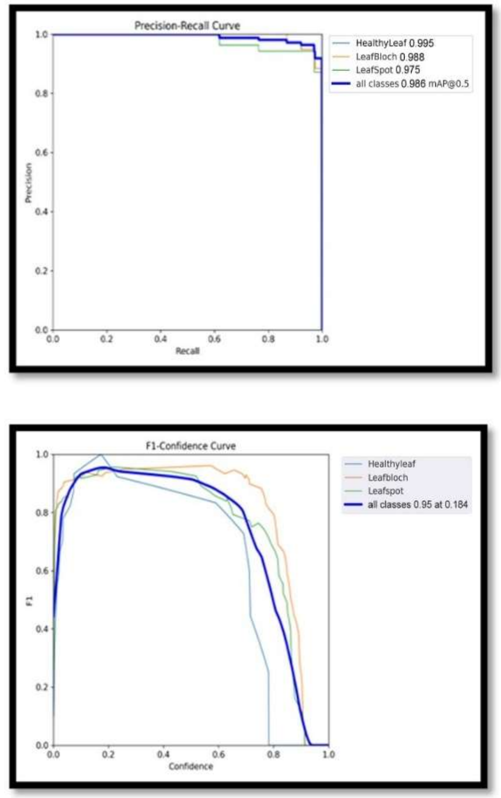


Figure 12:Curcuma longa leaf disease class detection performance with yolov5 model

Figure 13: Results of Curcuma longa Diseased leaf detection with bounding boxes using yolov5



(A)

(B)

Figure 14: Curcuma longa leaf disease Classification performance analysis (A)P-R Curve (B)F1Confidence ofYolov5 at 250 Epochs.

8.2. Curcuma longa leaf Disease Detection using Yolov8

The YOLOv8 method for Curcuma longa leaf disease detection has achieved classification accuracy for the Curcuma longa dataset, specifically for healthy leaves (98.5%), leaf blotches (89.8%), and leaf spots (88.5%). All three classes of Curcuma longa leaf datasets yielded a mean accuracy precision (mAP) of 85.1%. Figure 16 displays the detailed gain and loss graphs using Precision and Recall (PR), and Figure 18 (A-B) shows the ROC curves that show a very high F1 score of 83.0% at 0.20.

In Yolo v8 five metrics are used to calculate the performance analysis of Curcuma longa Disease leaf recognition from a multi-class Curcuma longa leaf dataset: coordinate loss, object-ness, classification, accuracy, and recall. Figure 15 displays the labeling of Leaf Bloch, Leaf spot, and healthy leaf classes of Curcuma longa leaf data throughout the training period. Figure 17 shows the bounding box of the Leaf Bloch, Leaf spot, and healthy leaf from the Curcuma longa dataset, YOLOv8 identified Disease leaf, and Figure 18 (A&B) shows the Curcuma longa leaf classification peak performance for YOLOv8 utilizing the PR curve and F1-score. The Leaf class confusion matrix and the peak performance metrics for YOLOv8Curcumalonga leaf Classification at 300 epochs are shown in Figure 18.

8.2.1. Training Loss

The training loss is a statistic that measures how well the model's predictions match the ground truth leaf disease in the context of Curcuma longa leaf training for the YOLOv8 (You Only Look Once version 8) object identification model. The loss function of YOLOv8 consists of a number of parts that each focus on a distinct facet of the object identification problem. Training loss uses the objectness, box validation, and classification for detecting the diseased leaf with a loss function.

a. Box validation

The box validation displays the accuracy of the Curcuma longa leaf disease classification training at 0.048359, The extent to which the projected bounding box encompasses the Diseased leaf class object, together with the model's proficiency in accurately identifying the exact location of the disease placed in the Curcuma longa Dataset of a Sick leaf data.

b. Objectness

Object-ness loss quantifies an object's probability of existing in a region of interest (RoI). With a relatively small object-ness Curcuma longa leaf data training loss of 0.014935, the Curcuma longa leaf dataset is considered to have a diseased leaf match for the object presence in the Sick leaf data.

c. Classification

The classification loss measures the accuracy of the method's estimates for a diseased leaf spotted inside the leaf class. The function of loss for the Curcuma longa leaf data training category value is 0.007425, suggesting a high level of efficiency in identification at this low value. The precision score of 0.860379 indicates that the model of prediction accurately identifies the designated disease class, the recall value of 0.804229 shows that the Yolo8 effectively finds all instances of the targeted disease category, while the mAP of 0.849624 signifies outstanding classification performance.

Figure 15: Curcuma longa leaf classes labelling during the Training phase (PANET) using Yolov8.

8.2.2. Validation Loss

The deep learning model uses validation loss as a metric to evaluate its performance on the Curcuma longa dataset to identify the disease leaf data. A chosen portion of the Curcuma longa dataset especially serves as the validation set, confirming the model's functionality. Calculating the validation loss using the sum of the errors on each diseased and healthy leaf sample in the validation set, just like we do for the training loss.

a. Objectness

Object-ness loss quantifies an object's probability of existing in a region of interest (RoI), the object-ness training loss on the Curcuma longa leaf dataset is 0.014286, it is considered a satisfactory match, indicating the presence of a disease and healthy leaf data in the picture frame shown in Figure 18.

b. Box validation

The box loss signifies whether the Diseased class leaf data is encompassed by the predicted bounding box, the effectiveness of the model in pinpointing to precise location of a diseased leaf data, and its training accuracy of classification is 0.034681 (Figure. 16).

c. Classification

A measure of the algorithm's prediction accuracy for diseased leaf data on a Curcuma longa leaf class is called classification loss. The training classification value's loss function is 0.007168, a meager value that produced high classification accuracy. The precision rating of 0.819375 indicates that the predicted model accurately predicts the Disease leaf class and Healthy leaf class. With a recall score of 0.814229, the Yolo5 model performed well in locating every Leaf in the class of targeted Curcuma longa disease leaf. With a mean Average Precision (mAP) of 83.1% and the categorization is quite excellent which is shown in Figure 18.

Journal of Theoretical and Applied Information Technology
15th March 2025. Vol.103. No.5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

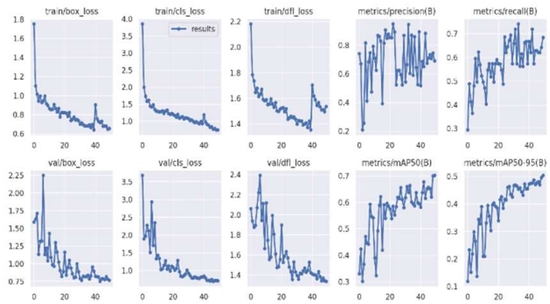
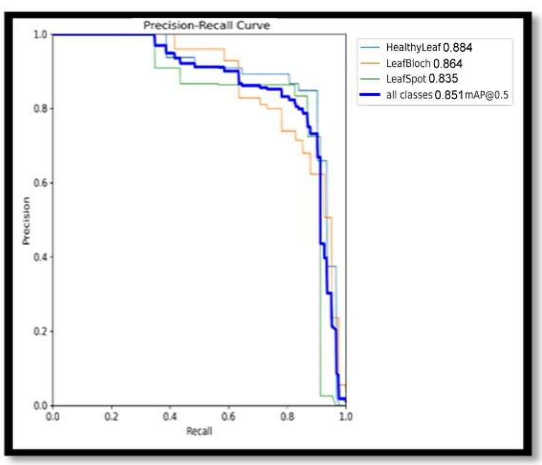
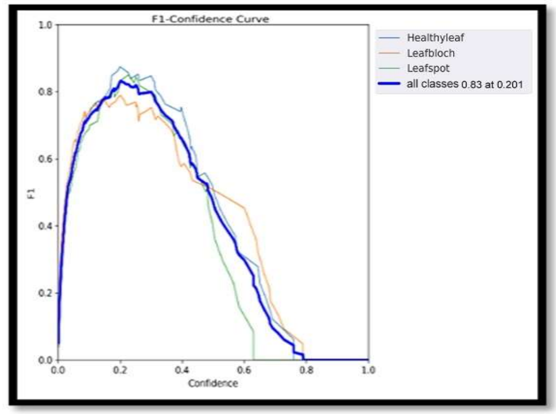


Figure 16: performance analysis of Curcuma longa leaf Classification at 300 epochs using Yolov8.

Figure 17: Curcuma longa Diseased leaf detection with bounding boxes using yolov8 result on Curcuma longa leaf dataset.



(A)



(B)

Figure 18: Curcuma longa leaf disease Classification performance analysis (A) P-R Curve(B)F1 Confidence ofYolov8 at 300 Epochs.

Table 1: YOLOv5 and YOLOv8 Training and validation results

S.No	Feature		Yolov5	Yolov8
1	@mPA_0.5		98.1	85.1
2	Epoch		250	300
3	Training	Box Loss	0.026473	0.048359
4		Objectnessloss	0.017245	0.014935
5		Classification loss	0.007152	0.849624
6	Validation	Boxloss	0.033569	0.034681
7		Objectnessloss	0.860379	0.014286
8		Classification loss	0.804229	0.819375

8.3. Epochs Impact

Figures 19 and 20 indicate that epochs effect on the Curcuma longa dataset Precision, Recall, F1-Score, and P-R curve. The YOLOv5 and v8 algorithm computes accuracy for every 25 epochs starting from 25 to 300 epochs. Tables 1 and 2 show the peak classification accuracy of the Curcuma longa leaf dataset at 250 epochs in YOLOv5 and 300 epochs in YOLOv8. Figure 19 shows that Yolov5 has accuracy with lower epochs, whereas Yolov8 had greater accuracy with intermediate epochs between 50 and 200. According to Figure 20, recall is usually greater than precision, followed by PR and F1 Score.

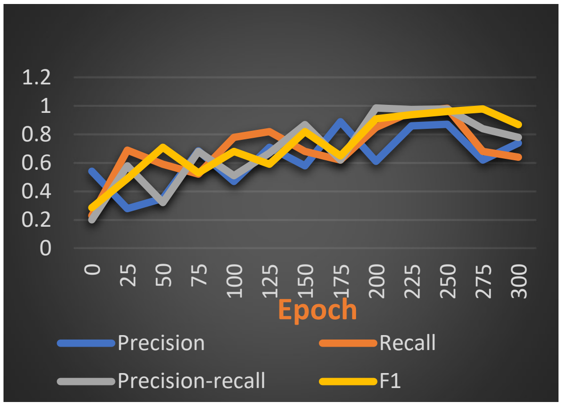


Figure 19: YOLOv5 performance analysis of Precision, Precision-recall, Recall, F1-score, with epochs.

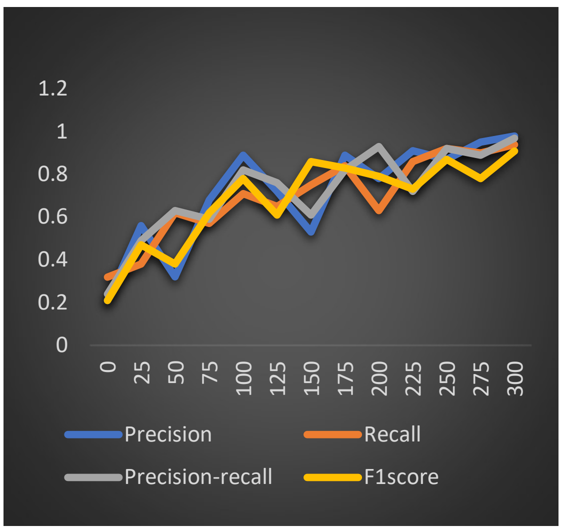


Figure 20: YOLOv8 performance analysis of, Precision, Precision-recall, Recall, F1-score, with epochs.

8.3.1. Precision

YOLOv5 outperforms YOLOv8 in all accuracy tests, as seen in Table 1. YOLOv5 has 68%, 85%, and 89.1% precision for Leaf spot, Leaf blotch, and healthy leaf, whereas YOLOv8 had 61%, 56%, and 42%. Overall, YOLOv5 has 12.5% more true positive values than YOLOv8 in Curcuma longa leaf class detection. Both models identify all Curcuma longa leaf classes, Yolov5 attains 8% more than YOLOv8. The diseased leaf class is identified more effectively with higher precision in Yolov5 than the Yolov8.

8.3.2. Recall

YOLOv5 outperforms v8 in Leaf spot, Leaf blotch, and Healthy Leaf recognition. The recall value of Leaf Spot and Leaf Blotch is superior for YOLOv8. When detecting three leaf classes, YOLOv5 and YOLOv8 vary by 1.1%, 0.1%, and 0.45%. YOLOv8 improved leaf spot and leaf blotch class recall by 3% over YOLOv5. YOLOv5 detects leaf disease classes with reasonable accuracy, but YOLOv8's enhancements in algorithm efficiency and feature extraction have led to more precise classifications.

8.3.3. F1-Confidence Score

The F1 confidence curve shows the highest F1 score, 0.86, with a confidence threshold of 0.523. This indicates that at this specific threshold, the model achieves an optimal balance between precision and recall, making it highly effective for the given classification task. As the threshold varies, the F1 score may fluctuate, highlighting the importance of selecting an appropriate confidence level for performance evaluation. YoloV8 detects leaf disease with 0.523 confidence.

8.3.4. Precision (mAP@0.5andmAP@0.5 to 0.95)

As shown in Table 1, Yolov5 consistently outperformed Yolov8 in terms of accuracy, with 98.6% and 66% of the class achieving mAP@0.5 and mAP@0.5 to 00.95, respectively. This significant difference highlights the effectiveness of Yolov5 in object detection tasks, suggesting that it may be a more reliable choice for applications requiring high precision. Overall, YOLOv5 outperformed YOLOv8 by 86.1% and 339%, respectively. The mAP values indicate the model's efficacy in identifying an object inside a frame via a comparison with the recognized area to the level of the truth boundary box at an IOU value of 0.5. The 12.5% difference between the mAP@0.5 of YOLOv5 and YOLOv8 shows how accurately and precisely the model diagnoses illnesses in comparison to ground truth objects. When comparing YOLOv5 to YOLOv8, the mAP@0.5 to 0.95 demonstrates a higher performance of 2.7% average mAP difference at various thresholds. Except for recall scores during testing, all performance indicators indicate that the YOLOv5 performs excellently over the YOLOv8 model. Testing results (Table 2) show that YOLOv5 outperforms YOLOv8 in terms of recall, precision, and detection accuracy, especially when used in production.

Journal of Theoretical and Applied Information Technology
15th March 2025. Vol.103. No.5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2: YOLOv5 and YOLOv8 Performance analysis of Curcuma longa leaf disease Classification.

S. NO.	Features		Classification Accuracy						Difference YOLO (V5-V8)		
1	Model		YOLOV5			YOLOV8					
2	Class Name		Leaf spot	Leaf Bloch	Healthy	Leaf spot	Leaf Bloch	Healthy	Leaf spot	Leaf Bloch	Healthy
3	Performance Metrics	precision	0.609	0.859	0.870	0.50	0.43	0.54	0.09	0.50	0.48
4		Recall	0.981	0.98	0.979	0.92	0.91	0.89	0.12	0.01	0.05
5		Accuracy Precision	0.985	0.978	0.985	0.874	0.846	0.853	0.11	0.142	0.14
6		mAP_0.5	0.986			0.861			0.125		
7		mAP_0.5:0.95	0.66			0.39			0.27		

9. DISCUSSION

Khan et al. (2021) compared GoogLeNet, AlexNet, and SqueezeNet in their study. Using EEG data to adjust hyperparameters, they obtained 94.99%, 94.61%, and 94.09% accuracy. The detection study shows AlexNet beats GoogLeNet and SqueezNet. They ignored optimizers and focused on epochs and learning rate. The present work solely fine-tunes hyperparameters and investigates optimizers' effect on training accuracy [23]. Ullah et al. (2022) tested AlexNet, ResNet18, and SqueezeNet on 4333 pictures of eight road fracture classifications. This experiment kept training and testing pictures constant throughout each epoch. Optimizer selection was not the investigation's main emphasis. ResNet18 has 85.2% accuracy. The suggested method focused on training issues with GoogLeNet, SqueezNet, and ResNet-50. We did this by fine-tuning hyperparameters and focusing optimizers like ADAM, RMSProp, and SGDM [24]. Ashhar et al. (2021) tested deep learning models including GoogLeNet, SqueezeNet, DenseNet, ShuffleNet, and MobileNetV2 on CT scan lung cancers. The GoogLeNet model yielded 94.53% accuracy [25]. They ignored ResNet-50 and focused on validation accuracy. In 2022, Dahiya et al. focused on training accuracy using the Plant Village dataset of 20,640 photos of 15 classes and 3 species: pepper, potato, and tomato. These datasets were applied to eight deep learning architectures: AlexNet, GoogLeNet, MobileNet, ResNet-18, ResNet-50, ResNet-101, ShuffleNet, and SqueezeNet. Hyperparameters included epochs, learning rate, small batch size, and optimizer. Only ADAM and SGDM optimizers are used, and RMSProp is ignored. Epochs span from 30 to 50. GoogLeNet successfully identifies bigger datasets better than the other eight deep learning models. Only two optimizers and three epochs limit them. The present study used L2Norm, Global-L2Norm, and Absolute optimizers on six epochs from 25 to 50. The batch size was 32 and vector distance algorithms were used. GoogLeNet is the best classifier, according to Dahiya et al. Our study indicated that ResNet-50 is the best model for categorizing the smaller ill leaf dataset due to vector distance model variation [26].

Testing of the Curcuma longa leaf dataset reveals epoch-to-epoch differences in categorization accuracy. Based on the investigation, YOLOv5 and YOLOv8 had almost identical behavior throughout epochs. On the other hand, YOLOv8 earned 86.1% classification accuracy at 300 epochs, whereas YOLOv5 reached 98.6% at 250 epochs. When compared to YOLOv5, the mAP is much smaller, even though YOLOv8 obtained greater accuracy at lower epochs Furthermore, the YOLOv8 model achieves 250 frames per second (fps), while the YOLOv5 model achieves 140. YOLOv8's higher frame rate leads to an accuracy drop of 86.1%. In contrast to Haitong Pang et al.'s work, which used YOLOv4 to reach 92.86% accuracy, this research used YOLOv5 to obtain 5.74% greater accuracy. C. J. Chen et al. (2023) YOLOv3 leaf disease recognition accuracy is 93%; the proposed research outperformed it by 5.6%. In comparison to earlier efforts, the suggested technique yields relatively high overall results.

Selcuk et al. (2023) have concentrated on the detection of mobile UI and found that YOLOv8 has outperformed YOLOv5, where mAP is 3.32%

higher. In the current research, YOLOv8 performed better than YOLOv5 on the Curcuma longa dataset for diseased classes, which is a novel performance evaluation on medical plants. Chitraningrum et al. (2024) did a study on YOLO detection, focusing on YOLOv5 and YOLOv8 on vegetable crops such as corn leaf disease. They found that YOLOv8 had a high accuracy rate of 96.5%, but the proposed work achieved a higher accuracy rate for YOLOv8 with 98.2% at 250 epochs, which is the highest ever. A study by Muriyah et al. (2024) compared how well YOLOv5 and YOLOv8 could find people. They found that YOLOv5 was the most accurate, with a precision accuracy of 82.89%. But still, YOLOv8 is suggested by the researcher. Chathurya et al. (2024), as discussed in various detection applications on turmeric detection, used a machine learning algorithm on the turmeric dataset and achieved 91% classification accuracy, while the proposed work achieved 98.6% using YOLOv8. Devisurya et al. (2022) used YOLOv3 for detecting the turmeric disease and achieved lower accuracy (97%) than the current work, and they used only one approach, but the current work evaluates the performance. Nandhini et al. (2016) performed disease identification on the turmeric dataset using 10-fold cross-validation using machine learning, like a sum, and achieved lower accuracy. Therefore, the proposed work is novel and achieves higher classification accuracy compared with the existing literature on the turmeric leaf dataset.

The YOLO v5 and v8 must reliably detect damaged and healthy Curcuma longa leaves for smart agricultural operations and crop yields. YOLO detectors identify diseased leaves to reduce disease. These methods boost yield and sustainability by reducing pesticide usage and crop losses. The YOLO deep learning method detects leaf diseases and improves farming. Similar Curcuma longa disease categories are difficult to identify. To explain these discrepancies, YOLO detectors evaluate each class's unique molecules. Deep learning algorithms identify leaf diseases and reduce agricultural losses in YOLO V5 and YOLO V8. We must analyze pictures from the Curcuma longa leaf dataset for disease detection. Image quality improves feature extraction accuracy and allows YOLO V5 and V8 model development, giving farmers and researchers timely information for crop management and yields. YOLO V5 and V8 identification is faster and more accurate than before. Evaluation in varied environments is crucial since they may drastically impact system performance. Using the Curcuma Longa leaf dataset, YOLO V5 and V8 algorithms can accurately identify leaf diseases by testing their robustness and dealing with image noise. The system detects plant development stages reliably. Environmental elements vary fast in agriculture; therefore, adaptability enhances system efficiency, crop management, and production optimization.

This study looked at the newest deep learning detection methods, such as YOLO V5 and YOLO V8, and found that the method that found diseases in the new Duggirala variant turmeric leaf dataset with the highest accuracy rate (98.1%) was YOLO V5. This is what the study's strength is. However, this work still needs to be more accurate so that it can be analyzed with the newest technologies to get a 99.9% success rate with the newly released YOLOV11 and YOLOV11 on the Duggirala variant turmeric leaf dataset. Additionally, testing the analysis with other turmeric variants and a wider range of classes is crucial, as it represents the weakest point of this work.

10. CONCLUSION

In South Asia, Curcuma longa is a highly prized medicinal and commercial crop. Farmers are experiencing financial losses due to a serious disease infestation on their Curcuma longa crop. The disease, caused by various pathogens, not only affects the yield but also diminishes the quality of the rhizomes, making them less marketable. As a result, researchers are urgently seeking effective management strategies to help farmers protect their crops and sustain their livelihoods. Identifying leaf diseases early on may help increase crop yield. The present research uses the YOLOv5 and YOLOv8 CNN models to detect leaf disease in Curcuma longa crops. The research examined three leaf classes of Curcuma longa. Leaf spots and leaf blotches are known to cause serious harm to the leaves of Curcuma longa crops. To identify Curcuma longa leaf illness, the research generated a fresh dataset of Curcuma longa leaves with three classes and used the Convolution Neural Network (CNN) YOLO v5 and v8 models to detect diseased leaves. The exploration of Curcuma longa leaf illnesses reveals significant advancements in the use of artificial intelligence for agricultural diagnostics. By generating a fresh dataset categorized into three distinct classes, researchers have laid the groundwork for a more nuanced understanding of plant health. The implementation of CNN YOLO v5 and v8 models demonstrates the potential of deep learning techniques to accurately identify and classify leaf ailments. This innovative

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

approach not only enhances the efficiency of disease detection but also contributes to sustainable agricultural practices, underscoring the vital intersection between technology and botany in safeguarding crop health. For both of the main categories of Curcuma longa Leaf diseases, the Yolov5 algorithm outperforms the Yolov8 method. On the other hand, version 8 has greater detection performance than version 5 at lower epochs, according to the data. Since Yolov8 has greater frames per second (fps) than Yolov5, the calculation time in Yolov5 is longer than in Yolov8. According to the research work, YOLOv5s' mAP performance is 12.5% higher than YOLOv8's. The current study details the best deep learning strategy for identifying ill Duggirala turmeric leaves. This investigation identified turmeric leaf (Duggirala variation) diseases early. This study examined the latest deep learning detection algorithms, YOLO V5 and V8. The new Duggirala variety turmeric leaf dataset showed that YOLO V5 was highly accurate (98.1%) at detecting illnesses. This study's classification accuracy is the highest on the unique Duggirala Turmeric Dataset for leaf disease detection.

REFERENCES:

[1].HK Koh, AC Geller , VanderWeele TJ. "Deaths from COVID-19. " *Jama* volume. 325 ,no.2 ,2021 , pp.133-134.

[2].Y Alimohamadi, M Sepandi, M Taghdir, H Hosamirudsari."Determine the most common clinical symptoms in COVID-19 patients: a systematic review and meta-analysis." *Journal of preventive medicine and hygiene* ,volume.61, no.3, 2020, E304.

[3].A Balkrishna, AB Bhatt, P Singh, S Haldar. "Comparative retrospective open-label study of ayurvedic medicines and their combination with allopathic drugs on asymptomatic and mildly-symptomatic COVID-19 patients." *Journal of Herbal Medicine,* no.29, 2021,pp.100472.

[4].N Gangal, V Nagle, Y Pawar, S Dasgupta. "Reconsidering traditional medicinal plants to combat COVID-19." *AIJR Preprints,* volume.34, no.1,2020,pp.1-6.

[5].F Babaei, M Nassiri-Asl, H Hosseinzade. "Curcumin (a constituent of turmeric): New treatment option against COVID-19". *Food science & nutrition*, volume.8,no.10,2020, pp.5215-5227.

[6].K Rajagopal, P Varakumar, A Baliwada, G Byran."Activity of phytochemical constituents of Curcuma longa (turmeric) and Andrographis paniculata against coronavirus (COVID-19): an in silico approach". *Future journal of pharmaceutical sciences*, no,6,2020, pp.1-10.

[7].A Vahedian-Azimi, M Abbasifard, F Rahimi-Bashar, PC Guest, M Majeed, A Mohammadi "Effectiveness of curcumin on outcomes of hospitalized COVID-19 patients"*A systematic review of clinical trials. Nutrients*, volume.14, no.2,2022,pp.256.

[8].VG Jadhav, PP Baviskar, SN Waghmare. "Export performance of Turmeric in India." *The Pharma Innovation Journal*,volume.11,no.1, 2022,pp.425-427.

[9].RK Verma, P Kumari, RK Maurya, V Kumar, RB Verma, RK Singh,"Medicinal properties of turmeric (Curcuma longa L.)", *A review. Int. J. Chem. Stud*, volume.6,no.4, 2018,pp.1354-1357.

[10]. NM, S.M., 2021. "Review on detection methods of turmeric disease and methodology using artificial neural network".

[11]. TK Reddy, M Dutta, "Impact of agricultural inputs on agricultural GDP in Indian economy".*TheoreticalEconomicsLetters*, volume.8, no.10, 2018,pp.1840.

[12]. M Hatanaka, J Konefal, J Strube, L Glenna, D Conner, "Data-driven sustainability: Metrics, digital technologies, and governance in food and agriculture". *RuralSociology*, volume.87,no.1, 2022, pp.206-230.

[13]. R Rajamohanan, BC Latha., "An Optimized YOLO v5 Model for Tomato Leaf Disease Classification with Field Dataset. Engineering", *Technology & Applied Science Research*, volume.13,no.6,2023, pp.12033-12038.

[14]. JAB Susa, WC Nombrefia, AS Abustan, J Macalisang, RR Maaliw, "Deep learning technique detection for cotton and leaf classification using the YOLO algorithm". In 2022 *International Conference on Smart Information Systems and Technologies (SIST),* pp. 1-6. IEEE.

[15]. Q Dong, L Sun, T Han, M Cai, C Gao, "PestLite: a novel YOLO-based deep learning technique for crop pest

detection". *Agriculture*, volume.14,no.2, 2024,pp.228.

[16]. V Ponnusamy, A Coumaran, AS Shunmugam, K Rajaram, S Senthilvelavan, "Smart glass: real-time leaf disease detection using YOLO transfer learning". In 2020 *International Conference on Communication and Signal Processing (ICCSP).*2020, July, pp. 1150-1154. IEEE.

[17]. MJA Soeb, MF Jubayer, TA Tarin, MR Al Mamun, FM Ruhad, A Parven, NM Mubarak, "Tea leaf disease detection and identification based onYOLOv7,(YOLOT)". *Scientificreports*, volume.13,no.1,2023,pp.6078.

[18]. ME Haque, A Rahman, I Junaeid, SU Hoque, M Paul, "Rice leaf disease classification and detection using yolov5". arXiv *preprint arXiv*:2209.2022. pp.01579.

[19]. R Zhu, H Zou, Z Li, R Ni, "Apple-Net: A model based on improved YOLOv5 to detect the apple leaf diseases". *Plants*, volume.12,no.1, 2022,pp.169.

[20]. CN Vanitha, S Malathy, P Shenbagavalli, SA Krishna, K Kavin, "Detecting Turmeric Taphrina Maculans Disease using Machine Learning Algorithms". In 2022 *International Conference on Applied Artificial Intelligence and Computing (ICAAIC).*2022, May.pp. 431-436. IEEE.

[21]. S Raina, A Gupta,"A study on various techniques for plant leaf disease detection using leaf image". In 2021 *International Conference on Artificial Intelligence and Smart Systems (ICAIS).*2021, March, pp. 900-905. IEEE.

[22]. R Ahmed, EH Abd-Elkawy, "Improved Tomato Disease Detection with YOLOv5 and YOLOv8". *Engineering, Technology & Applied Science Research*, volume.14,no.(3),2024, pp.13922-13928.

[23]. ID Khan, MH Khan, O Farooq, YU Khan. "A Comparative Analysis of Seizure Detection via Scalogram using GoogLeNet, AlexNet and SqueezeNet." *In 2021 Smart Technologies, Communication and Robotics (STCR)*, pp. 1-5.

[24]. Sathiya, V., M. S. Josephine, and V. Jeyabalaraja. "An automatic classification and early disease detection technique for herbs plant." *Computers and Electrical Engineering.volume*.100,no.1,2022,pp.108026.

[25]. Prathyusha, Kodamala, Aluri Jacob Solomon Raju, and Peddada Jagadeewara Rao. "Novel Malaria Risk Prediction and Mapping of Integrated Tribal Development Agency, Paderu Region, India, Using SAMRR." *Journal of the Indian Society of Remote Sensing* volume.52, no. 1,2024,pp.167-187.

[26]. Iren, Ecem. "Comparison of yolov5 and yolov6 models for plant leaf disease detection." *Engineering, Technology & Applied Science Research*.volume.14, no. 2, 2024,pp.13714-13719.

[27]. A Ullah, H Elahi, Z Sun, A Khatoon, I Ahmad, I. Comparative analysis of AlexNet, ResNet18 and SqueezeNet with diverse modification and arduous implementation. *Arabian journal for science and engineering,* volume,47,no.2, 2022,pp 2397-2417.

[28]. SM Ashhar, SS Mokri, AA Abd Rahni, AB Huddin, N Zulkarnain, NA Azmi, T Mahaletchumy T. Comparison of deep learning convolutional neural network (CNN) architectures for CT lung cancer classification. *International Journal of Advanced Technology and Engineering Exploration*, volume.8,no.74, 2021,pp. 126.

[29]. S Dahiya, T Gulati, D Gupta. Performance analysis of deep learning architectures for plant leaves disease detection. Measurement: Sensors, volume.24,2022,pp.100581.

[30]. MP Mathew, TY Mahesh, "Leaf-based disease detection in bell pepper plant using YOLO v5". *Signal, Image and Video Processing*,2022, pp.1-7.

[31]. Z Chen, R Wu, Y Lin, C Li, S Chen, Z Yuan, S Chen, X Zou, "Plant disease recognition model basedonimprovedYOLOv5". *Agronomy*, volume.12,no.2,2022,pp.365.

[32]. N Chitraningrum, L Banowati, D Herdiana, B Mulyati, I Sakti, A Fudholi, H Saputra, S Farishi, "Comparison Study of Corn Leaf Disease Detection based on Deep Learning YOLO-v5 and YOLO-v8". *Journal of Engineering and Technological Sciences,* Vol. 56, No. 1, 2024, pp.61-70.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[33]. V Gopi, and D Rajesh. "Novel deep learning training optimizer issues analysis to detect seashore high and low tides". *Ecological Engineering & EnvironmentalTechnology* .volume.26,no.4,2025, pp.13–33.

[34]. T Yang, S Zhou, A Xu, J Ye, J Yin, "An approach for plant leaf image segmentation based on YOLOV8 and the improved DEEP LABV3+". *Plants*, volume.12, no.19,2023, pp.3438.

[35]. R Sujatha, JM Chatterjee, NZ Jhanjhi, "Performance of deep learning vs machine learning in plant leaf disease detection". *Microprocessors and Microsystems,* volume.80,2021, pp.103615.

[36]. P Kaur, S Harnal, V Gautam, MP Singh, A novel transfer deep learning method for detection and classification of plant leaf disease. *Journal of Ambient Intelligence and Humanized Computing*, volume.14,no.9,2023, pp.12407-12424.

[37]. Y Wu, X Feng, G Chen. Plant leaf diseases fine-grained categorization using convolutional neural networks. IEEE Access. 2022 Apr ,pp.41087-96.

[38]. KM Hosny, WM El-Hady, FM Samy, E V rochidou, GA Papakostas, "Multi-class classification of plant leaf diseases using feature fusion of deep convolutional neural network and local binary pattern". *IEEE Access*, volume.11,2023, pp.62307-62317.

[39]. P Lambu, R Duvvuru. "Training Issues in Classifying Urban Flood Object Detection–A Deep Learning Study." Ecological Engineering & Environmental Technology (EEET) volume.25, 2024,pp 10.