MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 12-17

Automated Multi-Crop Leaf Disease Detection Using Deep Learning Models and YOLO Based Object Detection

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Abstract:

Crop diseases have been the biggest challenges in attaining food security, thus highlighting importance of automated detection systems for crop diseases at early stages. Manual visual inspection is not effective, appropriate, or feasible for cultivating large areas of crops, relying on expert knowledge that is mainly based on observation. This article provides a comparative deep learning approach in accurately plant leaf detect diseases using image data, thus addressing the challenges associated with traditional visual inspection methods. This article presents a proposed framework that compares the performance of a number of pre training models, including Res Net, VGG, Mobile Net, Dense Net, Efficient Net, all have been pre trained to the image datasets of leaf images, along with a custom CNN approach to accurately detect plant leaf diseases using image data. Standard image preprocessing techniques have been applicable to enhance the performance of proposed approach, thus eliminating the chances of overfitting, leading to increased accuracy in classifying leaf images under varying environmental conditions. In addition, real-time object detection is achieved using YOLO, thus accurately localizing disease areas on leaf images. In addition, to enhance real-world applicability, the proposed approach is implemented using a web-based system, thus making it feasible for integration with existing systems in agriculture. Experimental results show that transfer learning models outperform the custom CNN approach in terms of accuracy, whereas YOLO is used to accurately localize disease areas on leaf images.

Keywords: Deep learning, Plant disease detection, YOLO, Convolutional neural networks (CNN), Transfer learning, Image preprocessing, Data augmentation, Object detection, Precision agriculture, Web-based deployment.

1. INTRODUCTION

Agriculture plays a fundamental role in sustaining global food security and supporting the livelihoods of billions of people around the world yield and quality, leading to economic losses for It serves as the primary source of food, raw materials, and employment, particularly in developing economies. Despite continuous advancements in agricultural practices and technologies, crop productivity remains highly vulnerable to plant diseases. If not detected and treated early, Diseases can impact both greatly. Farmers and their profit margins face losses due to quality yield. When detected and treated at an, food availability will not. Beginning phase. As the population of global continues to grow, ensuring healthy crop production has become an increasingly critical challenge.Among the various parts of a plant, leaves serve as one of the most important indicators for disease diagnosis. Many plant diseases manifest symptoms that are visible on leaf surfaces, such as discoloration, wilting, lesions, spots, mild growth, and irregular texture patterns. These visual cues enable the images of leaves to serve as an important source of information in identifying plant health conditions. Timely and effective identification of diseases on leaves enables farmers to implement appropriate preventive measures to avoid excessive use of pesticides usage, and minimize crop damage. Therefore, the developed efficient and reliable leaf disease detection systems is essential for improving agricultural sustainability and productivity [1], [3].Identification of plant diseases has usually depended on. A manual inspection conducted by trained agricultural specialists. botanical disease specialists. While expert-based diagnosis can yield reliable results, it presents several inherent limitations. Manual inspection is labour-intensive, time-consuming, and costly, especially when applied to large agricultural fields. In many rural and remote regions, access to skilled experts is limited, often resulting in delayed diagnosis or incorrect treatment decisions. Additionally, visual assessment is subjective in nature and may vary from one expert to another. This subjectivity becomes particularly problematic when disease symptoms are subtle or when multiple diseases exhibit similar visual characteristics [2], [12] These issues make it abundantly clear. the necessity of automated and scalable plant disease detection applications.

Recent developments in ai in particular. Advancements in deep learning have opened up new possibilities. Automated diagnosis of plant diseases. Neural network models. In the realm of computer vision, innovations have shown promise. Typically involves the performance of a computer vision system. distinguishing images, detecting objects, and recognising patterns. The most important technique in computer vision is the use of convolutional neural networks (CNNs) since It can learn features directly from the image pixel values. not needing any feature engineering. This makes them suitable for analyzing images of plant leaves because the characteristics of the diseases can vary significantly in terms of shape, color, size, and texture [4], [15].Many research studies are conducted to. CNN-based models for plant disease classification leaf. Not needed Researchers demonstrated the potential of DNNs to do deepfake detection. identify plant ailments with images of the leaves surface. which is more accurate than typical machine learning. notables. Deep learning models were further developed. According to Ferentinos [3], he assessed the CNN models for. various crop varieties. These studies have shown the potential of CNN in capturing the complex patterns related to plant diseases. However, the earlier models were found to have limitations in terms of the use of shallow models or small datasets.

To reduce the requirements of the data and improved to the performance of the models, transfer learning is increasingly being employed in agricultural image processing. Transfer learning relies on. Fine-tuning of pre-trained AI model that analyse large data. compilations, including ImageNet. Pre-trained models can improve the performances. Models' performance on different data sets, smaller included. Data sets are used by harnessing characteristics learned through pre. Drills. ResNet, VGG, and other common pre-trained models. MobileNet, DenseNet, and EfficientNet were used to Enhance the models' performance in agricultural image. Including the plant disease classification problems [5, 6, 7, 8, 9] The performance of several was compared by Too et al. [2]. Models to identify plant diseases using transfer learning Demonstrating fine-tuned deep learning's superiority in issues. models with respect to other models that were trained. the accuracy, efficiency in training, and speed of convergence.The majority of studies have also reported high classification accuracies for deep learning-based classification methods. However, most have used image-level classification, where a single disease is classified over the entire image. The exact region is not specified. This is a drawback since a farmer or Agri professional needs to visually examine the region to assess the extent of damage and use the most effective treatments. This problem is addressed by object detection methods. YOLO Version8 is a highly effective object detection algorithm. It is specifically designed to work in real-time. Unlike other methods that use region-based detection and are computationally expensive, YOLO detects objects in a single pass. Hence, it is highly effective for real-time applications. YOLO is highly effective in computer vision applications and has been used for detecting objects such as fruits, pests, and diseases in plants. Hence, a combination of object detection and CNN-based classification would be a highly effective system for detecting plant diseases. Another drawback is that most studies have not implemented their methods in practical applications. Most have tested their methods in a controlled environment. However, a practical application needs to be user-friendly and accessible to a farmer. Hence, a web application or RESTful API would be a highly effective way to implement a disease detection system.

Inspired by the above-identified limitations, the present study proposes a wide-ranging deep learning framework, targeting leaf disease classification for various crops and real-time object detection The suggested framework analyses the.

Evaluation of a custom CNN against competitive benchmarks. Techniques for transfer learning in a unified setting. To enhance the system's robustness, image preprocessing and augmentation.Methods are used to reduce overfitting and increase the effectiveness of the system Performance comparison is carried out using several metrics including exactness.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Additionally, a YOLO-based object detection module is integrated into the framework to localize the disease regions in the leaf images in real-time. This will enhance the quality. Helps make informed decisions by understanding the output. A Flask framework integrates deep learning models through a web app.

The goal of this project is to develop a web application and a RESTful API to demonstrate the real. Potential global application of the proposed automated approach. Plant sickness identification. The primary aim of this article is to aid in the creation of enhanced effective, accurate, and strategies Clever remedies for the automatic diagnosis of the plant Sicknesses.

2. LITERATURE REVIEW

The application of computer vision and ML in plant disease detection has witnessed tremendous growth in recent times owing to the need to develop more efficient tools for the next-generation agricultural revolution. Traditionally, plant disease detection has relied on the application of image processing coupled with traditional ML approaches. These approaches typically relied on features learned from images of plant leaves. These features included color histograms, texture patterns, and shape features. These features were then used and classifying the plant various diseases using ML technologies. Although these make highest results approaching to shown in plant detection in controlled environments, they were limited in that the performance of these approaches depended on the quality of features learned from plant images. Lighting variations, background conditions, and variations in leaf angles have proven to be obstacles to achieving satisfactory results in plant disease detection [12].

One of recent years' most important developments. CNNs are used for plant disease detection. A member of The initial advancements in identifying plant diseases were showcased by Sladojevic et al. Want to verify this pas, in which they demonstrated that plant diseases could be accurately detected from images of plant leaves using deep learning approaches. A new Progress in. As mentioned by Ferentinos, plant disease detection was exhibited in which. Various applications utilized Deep Learning approaches successfully. Using crop species to demonstrate the efficacy of deep learning in plant. diagnosing illnesses The rise of deep learning technologies. With the emergence of learning models, transfer learning is possible. In detecting plant diseases. Transfer learning is an effective strategy for. effective technique in plant disease recognition. Various transfer learning applications were shown by Too et al. methods for identifying plant diseases. The authors demonstrated that plant diseases could be accurately classified using various deep learning architectures such as VGG, ResNet, and Inception. The authors demonstrated that plant diseases could be accurately classified using deep learning approaches.

Apart from that, there has also been an interest in developing lightweight CNNs that can function in resource-constrained environments. MobileNet, developed by Howard et al., achieves maximum efficiency by using depth-wise separable convolutions. DenseNet, developed by Huang et al., improves feature mapping by densely connecting the features. Recently, EfficientNet, developed by Tan and Le,[24] has demonstrated that improving the depth, width, and resolution of the input can improve accuracy while maintaining efficiency.

There has been some theories about plant disease. There have been limited studies on classification of the image level. Place where diseases occur. Classification-based Most of the Methods categorize the diseases at the complete image scale. The diseases, however, do not mention their location. photos They classify the diseases in the complete data set. graphic level Object detection can be used to find location. The diseases in the pictures with the diseases themselves. A work whose any other example in object detection, as in [10], detects. illnesses in a single motion. This generates results almost instantly high precision YOLO-based approaches have also been successful in various applications in the field of farming, such as fruit detection, pest detection, and localization of diseases in plants. However, many of the existing works in the field of object detection are primarily focused on localization and do not offer classification comparisons and system deployment, which are essential in real-world applications.

Another issue that is identified in the existing body of work is the lack of implementation in real-world applications. Several researchers have presented their works and reported promising results in their experiments, but relatively few have implemented their systems and made their applications accessible to users. Kamilaris and Prenafeta-Boldú highlighted the necessity of implementing deep learning solutions in real-world applications in the field of agriculture to increase adoption of these solutions. Web interfaces and RESTful APIs are also possible solutions that can be implemented in plant disease detection systems, but these are also in their infancy in the existing body of work.In summary, a lot of work has shown that the. viability of CNNs and transfer learning for plant diseases. YOLO-based classification and further emphasized their potential. localization methods. However, many object detection-based works are primarily focused on localization and do not offer classification comparisons and system deployment.

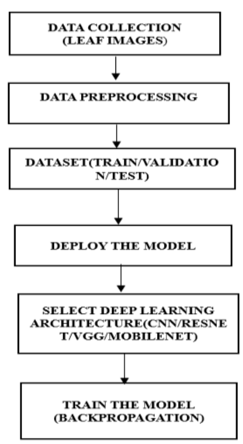

Fig 1 : Flow chart for deep learning models

3. METHODOLOGY

This segment will discuss a method that uses deep learning to automatically classify diseases in different crops and locate the occurrence of these diseases in real time [1], [3], [13The is already a one word sentence so it cannot be paraphrased. The method functions as a framework that integrates end-to-end. Preparing data sets and performing image pre-processing. Classification of objects based on data augmentation using deep learning. Real time detection, and finally implementation [15]. At its core, the framework is designed to provide an accurate and deployable solution for plant disease diagnosis that can work seamlessly in real-world scenarios [20], [21]. The entire process works from raw images of leaves to predictions in a straightforward manner that is computationally efficient and user-friendly.

3.1 System Overview

The suggested system has two modules, namely:
(i) disease classification module, and
(ii) disease detection and localization module.

The system will help in the disease classification module. Identify the disease in the leaf present in the image. The categorization. CNN will be employed to accomplish this task. [1], [12]. The convolutional neural network will be applied in two ways: the suggested CNN and various transfer learning techniques using the best available CNN architectures [2]. The disease class and the corresponding confidence level will be provided as the output of this module.In the disease detection and localization module, the system will be able to identify the regions in the leaf image that are infected with the disease. The YOLO technique will be used to perform the task [10], and the output will be the bounding box coordinates of the infected regions along with the class and confidence level.In the suggested system, the two modules will be integrated into a single framework, and the system will be deployed using a web application and RESTful API.

3.2 Dataset Preparation

A labeled dataset containing leaf images, covering different crops and types of diseases, is used for training and testing the proposed models [3], [20]. Each class in the dataset represents a different type of plant disease and/or a healthy leaf. The involvement of multiple crops and diseases in the dataset ensures that the proposed framework is able to generalize the data for a particular type of plant and different agricultural scenarios [13].

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
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To organize the dataset, the images are stored in a hierarchical structure in which each type of disease contains its own directory containing images of that particular type of disease.In order to avoid bias and data leakage, the data is split into a training set and a testing set. The training set is used to train the model parameters, and the testing set is used to evaluate the performance of the model.

3.3 Image Preprocessing

The images of leaves in real-world agricultural settings come in various sizes, lighting conditions, level of background noise, and orientations. Such changes can bring about adverse consequences. The effectiveness of deep learning models if mishandled. [13]. To make sure that all images have similar characteristics A series of standards that deep learning models can solve easily. All input images go through preprocessing steps [15].

Firstly, all images are resized to 224 × 224 pixels is because of many DL models, especially CNNs, use 224 × 224 as the input size for images [4], [5]. Other models that use transfer learning, such as VGG, ResNet, MobileNet, and EfficientNet, also require 224 × 224 as input size [5], [7], [9]. Resizing the images to 224 × 224 helps in ensuring that all images in the dataset have similar dimensions.The values of the pixels are images that. Brought to a common level to conform to a range. Normalization helps prevent numerical values. Fluctuations during training process of deep learning models have been reported in the literature [15]. It also aids in. enhancing the efficiency of neural network algorithms by. stopping internal covariate shift.

3.4 Data Augmentation

Agricultural photos and image sets are usually not large since it is hard to collect and annotate images. To mitigate this and enable better generalization for our model, we use a technique called data augmentation for our training set[13].

Data augmentation increases the quantity and variability of our training images by transforming existing ones. Our data augmentation process includes a series of transformations: random flipping, rotation, and adjustments to brightness and contrast. These operations are inspired by variations that could be caused by different angles of view, varying lighting conditions, and varying orientations of leaves.Through such exposure to a broader spectrum of images, overfitting is minimized and a more invariant representation is learned by our model[15]. This is important in our problem since diseases manifest under different conditions.

3.5 Deep Learning–Based Classification

3.5.1 Custom CNN Architecture

A custom convolutional neural network acts as a baseline classifier for measuring performance. ReLU activation functions are the convolutional layers allow the network to learn the detection of various features at different levels of complexity, ranging from basic images to complex images related to diseases[1]. The max pooling reduces the dimensions of the images. After the images are convolutional layers flattened for the fully connected layers, which make the final prediction of the disease. The custom convolutional neural network, although relatively simple to the compared complex learning models of transfer, shows the benefits a deep network and the use of pre-trained models[15].

Table 1: Comparison between Classification Models and YOLO Detection Model

Aspect	Classification Models (CNN/TL)	YOLO Detection Models
Task	Disease Identification	Disease Localization
Output	Disease Class Label	Bounding Boxes + Labels
Spatial Information	Not Available	Available
Interpretability	Limited	High
Real-Time Capability	Moderate	High
Practical Usefulness	Medium	High
Deployment Suitability	High	High

3.5.2 Transfer Learning Models

To encourage increased accuracy and better generalization, we test a number of top-performing transfer learning models. These models include ResNet, VGG, MobileNet, DenseNet, and EfficientNet models. These models have a strong history of performance in image recognition, including our problem, and all of them are pre-trained on ImageNet, a massive dataset of labeled images, including a wide range of image classes.Our approach will involve changing the last layers of these models, which are pre-trained, with new layers that are defined according to the number of classes in our disease dataset. This will speed up our approach because these models will perform better on our dataset due to the availability of data, despite the scarcity of data in our case, as they are pre-trained on large data sets them to perform better on the agricultural data set, especially since we are dealing with scarce data.The proposed transfer learning approach is one of the best methods for plant-leaf disease detection from images, especially when data is scarce. This is unlike the traditional method where we train our network on amounts of the large of data available which in not the case in this problem. We instead use the pre-trained models, which are trained on large amounts of data, including the ImageNet database, to perform the task at hand. These models are able to capture the features present in the data, including the edges, textures, and basic shapes, which we can utilize to perform the task. This speeds up allowing the model that the learning process, to converge to the solution more quickly, giving us a stable model.In this study, we explore some of the cutting-edge transfer learning techniques to determine the best one to be used in the classification of the diseases on the leaves. Deep residual learning is the best technique to be used when we want to train our deep network, with the best-performing model in this category being the ResNet model. The DenseNet model is also the best to be used since it promotes dense connections. The MobileNet model is the best when we are dealing with scarce data, while the EfficientNet model is the best when we want to obtain high-performance results with minimal complexity.It is a technique of Transfer learning that differentiates itself in the efficient classification of plant leaf diseases, particularly when the creation of a large labelled dataset in the field of agriculture proves to be difficult. Transfer learning has been shown to provide high accuracy without requiring a lot of time for training. When measuring of different models to the performance the depth of the models is not the only determinant of performance. The most important determinant of performance is the ability of the models to generalize. The presence of different lighting conditions, backgrounds, and orientations of the leaves all affect the performance of the models.

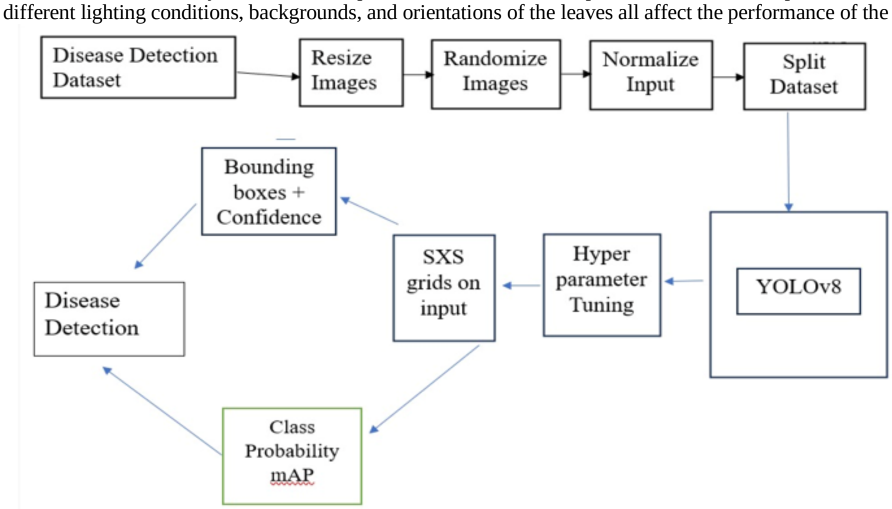

Fig 2. Block Diagram for leaf disease detection using Yolo

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 12-17

Table 2 : Comparative Analysis of Classification vs Detection Models

Model	Accuracy	Precision	Recall	F1-Score	Training Time
ustom CNN	78.45	0.79	0.78	0.78	42.6
VGG16	85.27	0.86	0.85	0.85	138.4
Res Net 18	86.92	0.87	0.87	0.87	96.8
ResNet50	90.34	0.91	0.90	0.90	182.5
MobileNetV2	87.63	0.88	0.88	0.88	74.3
DenseNet21	91.18	0.92	0.91	0.91	165.7
EfficientNet-B0	92.46	0.93	0.92	0.92	128.4

3.6 Model Training

All classification models are trained with the Adam optimizer[15]. Adam combines the benefits of adaptive learning rate methods with the benefits of momentum methods to provide fast convergence to the optimal solution.Since this classification problem is a multi-class classification problem, categorical cross-entropy will be used as the loss function. The parameters of the model will be trained for a specified number of epochs to minimize the loss.[26]. overfitting to prevent and select the top-performing model, accuracy and loss will be monitored during training. The top-performing model will be saved and early stopping can be used in case there is no improvement in accuracy.

3.7 Performance Evaluation

To obtain a complete and comprehensive understanding of how the classifier is performing, we use different metrics: accuracy, precision, recall, F1 score, and confusion matrix[3]. Accuracy indicates how often we are getting it right in total; precision and recall show how good we are at identifying different disease classes and keeping false alarms low. The F1 score is a combination of precision and recall into one score, which is useful when we are not dealing with balanced data. The confusion matrix gives more detailed insight into how we are performing for different classes, showing where we are getting things mixed up an d helping us analyze the classifier's behavior in more detail. During training, we see that both training and validation curves are moving steadily toward convergence: we see a steady decrease in losses over epochs and a plateau in accuracy at high values, suggesting that we are not overfitting much. The system was efficient for use in real-time agricultural monitoring and for dealing with multiple leaves in complex backgrounds and different lighting conditions[20].

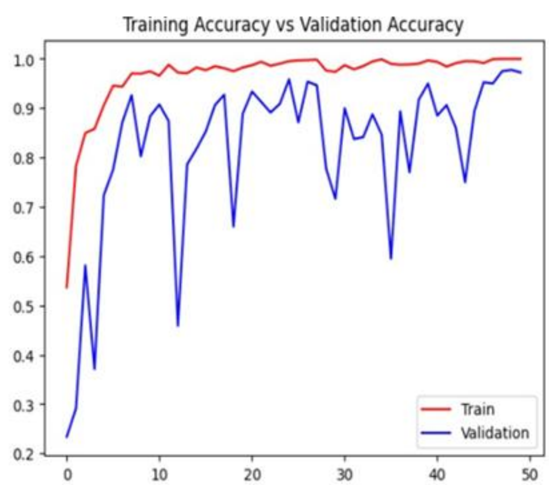

Fig 3. In addition to the result analysis for the model's accuracy graph

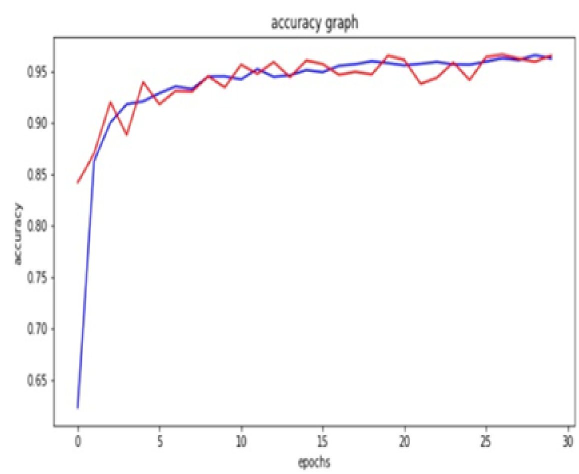

Fig 4. shows the result analysis for ResNet50 training

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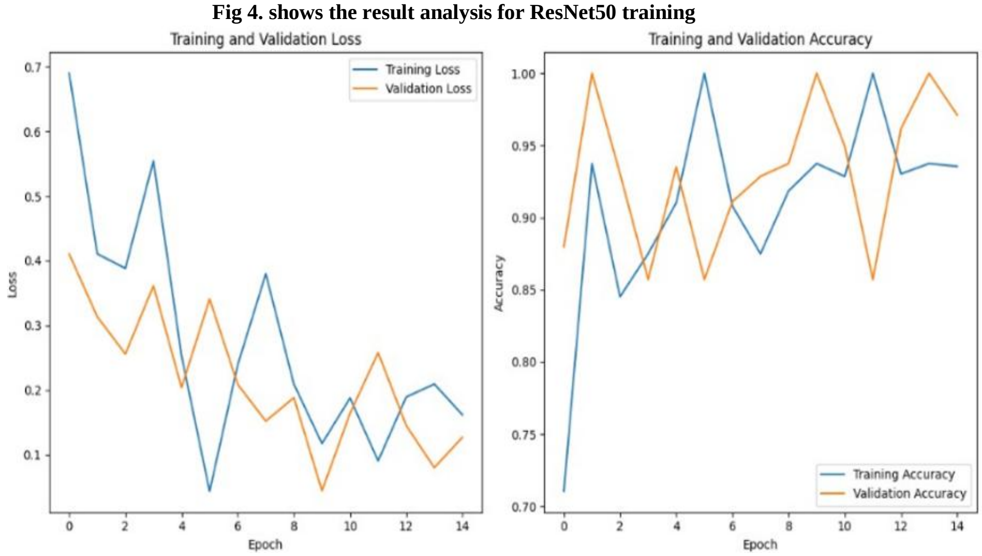

fig 5. result analysis of efficient net b3 model and loss graphs

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 12-17

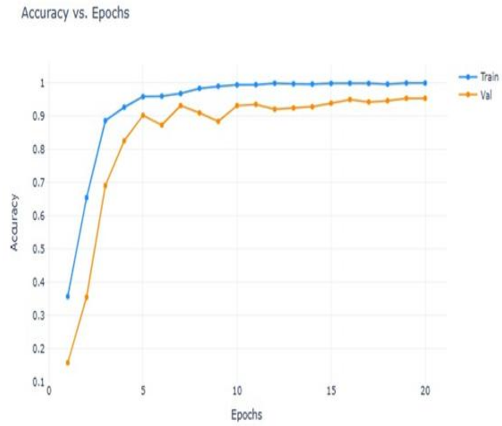

Fig 6. Dense Net accuracy graph in the figure

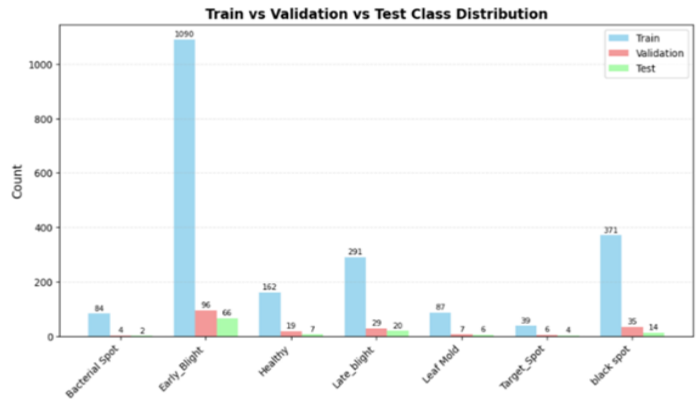

Fig 7. shows the result analysis for the YOLOv8 model, which includes training, validation, and test class disturbance graphs.

Fig 8 : Corn Gray Leaf Spot Disease

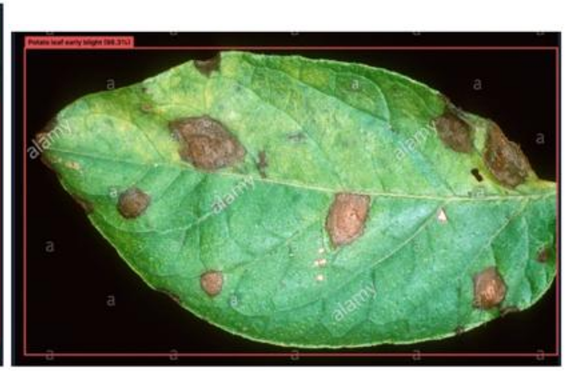

Fig 9. Potato Leaf early blight Disease detection

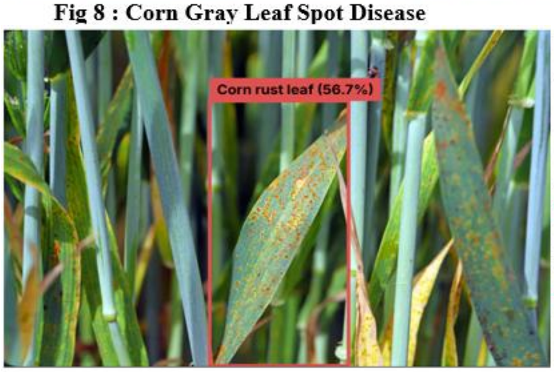

Fig 10. Common Rust on Corn Disease

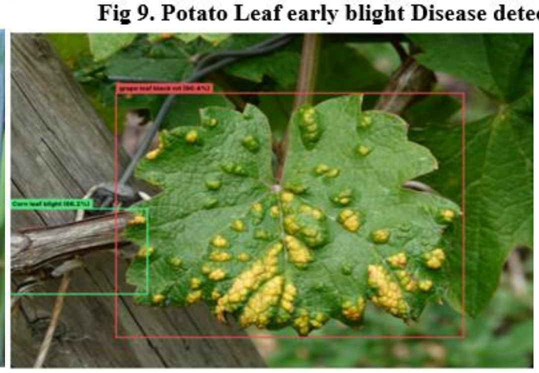

Fig 11. Grape Leaf Black Rot Disease

Fig 12 . Apple rust leaf disease

3.8 Real-Time Disease Detection Using YOLO

In addition to this, the framework also employs the object detector YOLO to locate the infected areas on the leaves[10]. YOLO is a one-stage detector, which means it processes the image in one forward pass. This makes it extremely efficient for real-world applications. It also returns bounding boxes, the corresponding diseases, and confidence levels. This makes it easy to visually locate the infected areas on the leaves, along with the spatial distribution of the disease. The next versions of YOLO, such as YOLOv8[19], improve the accuracy of the detector by employing multiscale features.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Vol. 36 Issue 1s, 2026, Pages: 12-17

3.9 Detection Result And Analysis

The performance of leaf disease detection framework is evaluated in this study from both qualitative and quantitative perspectives[20],[21],[22]. The YOLO model is tested with new images from different crops, backgrounds, and lighting conditions to see how well it generalizes and performs out of the box, without being specifically trained for those images. For the majority of the test images, the system is able to identify the affected areas of the leaf correctly, creating bounding boxes around the diseased areas and providing confidence values[10] according to the level of confidence in the predictions.

Looking at the results, it is clear that the system is able to identify multiple areas of disease infection on the leaf even when the infection is of different sizes, shapes, and even color intensities. The system also performs well in real-world scenarios and is able to handle shadows, partially occluded objects, and backgrounds without any issues. It is also able to identify some of the infection symptoms that are not easily visible to the naked eye, which is possible due to the power of deep learning features.

To evaluate the system from the quantitative point of view, some of the standard object detection metrics are precision, recall, F1 measure, and mean average precision[10],[14].

Combining localization and classification together provides significant benefits in terms of interpretability since the system is able to point out the areas of infection and also classify the type of infection, which is helpful in understanding the reason behind the prediction made by the system. From the experiments, it is clear that the proposed system is able to identify the leaf infection in real-time and is accurate in its predictions, making it suitable for use in real-world scenarios[20].

4. CONCLUSION

In the paper, a method for the detection of leaf diseases in plants is proposed based on deep learning. This is meant for going beyond. Incapacity of manual verification. It utilizes neural convolution. systems for identifying the differences between healthy. diseased ones leave behind. The study showed that it works. In classifying different plant diseases, detecting features using deep learning. Image preprocessing and augmentation have played an important role in enhancing the performance and generalization of the deep learning system, ensuring its effectiveness in different lighting and background conditions, as well as different orientations of the leaves, as would be the case in real-world scenarios. The use of automatic feature extraction in deep learning has helped the system learn the complex and subtle features of the diseases, which would otherwise have been missed in traditional manual checks.

Detecting diseases in crops thus demonstrates the power of this technology. Effective resolution in the area. deep learning is the use of in the early detection in plants diseases can have a number of advantages, including the early prevention of the disease, the reduction of the use of harmful chemicals, and the reduction of losses due to the disease. The practicality of the solution has been ensured by the use of the web, thus making it accessible to a wider audience. The use of deep learning in the early detection of diseases in plants has the potential to contribute to the precision agriculture development of by ensuring the use of data in driven decisions of the field, thus ensuring the sustainability of the practice.

In the future, the dataset could be expanded to include a broader range of plants and diseases. In addition, the system could be enriched by the inclusion of real-time data to take it to the next level, and environmental data could be incorporated to provide the system with another boost.

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