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INTEGRATED DEEP LEARNING FRAMEWORK FOR DISEASE CLASSIFICATION IN AGRICULTURAL COMPUTER VISION

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Abstract: *This study investigates the use of computer vision in agriculture, specifically focusing on classifying maize diseases. It explores the integration of machine learning and deep learning techniques, recognizing the limitations of using machine learning alone. The research highlights the need for additional image processing steps like preprocessing, feature extraction, segmentation, and augmentation to improve classification accuracy. The approach centers on the ResNet50 model, a deep learning architecture designed for automatic feature extraction. While deep learning excels at handling large datasets, it requires significant computational power. The proposed methodology employs a holistic preprocessing pipeline, beginning with image segmentation to convert raw images into labeled regions for detailed analysis. Data augmentation, using the U Square Net model, is applied before splitting the dataset to ensure an unbiased model evaluation. Techniques like Gaussian blur and normalization further enhance input features for the neural network. The model, built using PyTorch, combines the pre-trained ResNet50 model for feature extraction and effective pattern recognition. The study concludes with a thorough evaluation of the model's performance, demonstrating its potential to improve maize disease classification. This research offers a comprehensive framework for accurate disease identification in agricultural settings through the synergy of image processing and deep learning.*

Keywords: *Agricultural Computer Vision, Maize Disease Classification, Machine Learning, Deep Learning, Image Processing Techniques, Neural Network Modelling.*

1. Introduction

Machine learning has become crucial in the field of agriculture for effectively diagnosing diseases in maize plants. The primary objective of this project is to utilize advanced methodologies, specifically the integration of machine learning and deep learning paradigms, to improve our comprehension of maize disease classification. This method revolves around the ResNet50 Model, which is an artificial neural network renowned for its ability to automatically extract properties. This model is essential in the investigation of the detailed categorization of illnesses that impact maize plants. The methodology includes fundamental components, such as image segmentation, which is a technique used to divide images into distinct sections. This technique enhances the utilization of computational resources, leading to a more streamlined and targeted disease classification as shown in Figure 1. Data augmentation is an essential process in strengthening the model's robustness. By employing the U Square Net model, the process of picture data augmentation introduces variability to the dataset, hence improving the network's ability to adapt and perceive differences. Applying data augmentation before splitting the data helps ensure the accuracy of the evaluation procedure that follows.

The study explores the process of data transformation, which involves the application of Gaussian blur and normalization techniques. These changes enhance the quality of the input data, creating a dataset that is suitable for the requirements of the subsequent deep learning model. The analysis highlights the careful division of the dataset into training and test sets, which is an important step before using the PyTorch framework. This system enables the seamless incorporation of a customized neural network model with the pre-trained ResNet50 architecture, establishing a mutually beneficial connection between automated feature extraction and focused disease classification.

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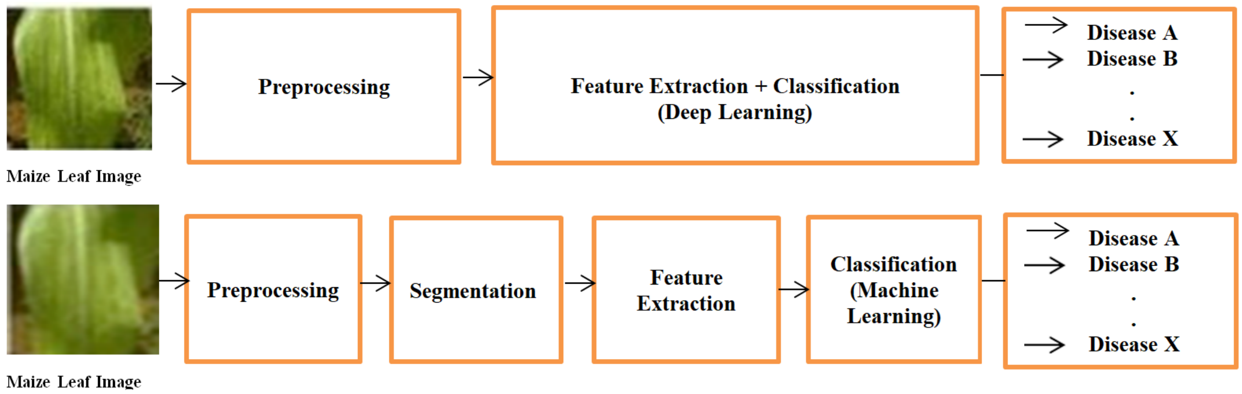

Figure 1: Maze Disease Image Classification using ML and DL

a. Background and Statement of problem

Maize, a vital global resource, confronts the menace of diseases that severely impact its productivity and quality, exposing shortcomings in traditional detection methods. This prompts a shift towards exploring computer vision, particularly deep learning, for accurate and automated disease identification. The ResNet50 Model, renowned for its feature extraction capabilities, emerges as a pivotal tool in this endeavour, although leveraging such advanced models requires a nuanced understanding of preprocessing, segmentation, and augmentation techniques. Consequently, this study aims to bridge research gaps by investigating the potential of deep learning for maize disease classification, merging insights from image processing and neural networks to enable reliable automated detection. Challenges in utilizing advanced machine learning and deep learning methods for disease classification include optimizing computing performance, enhancing dataset resilience through augmentation, refining data transformation techniques, ensuring methodological rigor in dataset partitioning, and seamlessly incorporating pre-trained models. Emphasis is placed on rigorously evaluating model effectiveness in real- world agricultural settings, with the overarching goal of enhancing precision agriculture practices and contributing to Sustainable Crop Disease Management.

b. Study objective

The primary objective of this project is to improve the precision of crop disease identification through a set of objectives. The main objectives involve gathering a heterogeneous dataset from different crops to guarantee the adaptability of the model. The U2Net approach will be utilized to achieve exact segmentation of afflicted leaf regions, facilitating accurate disease detection. The project aims to utilize modern techniques such as ResNet and Convolutional Neural Network (CNN) to categorize leaf images into healthy and sick groups. An essential part entails doing a comparative analysis of the methodologies, evaluating their performance using metrics like as Heat map, Precision, Recall, and F1-Score. This comprehensive evaluation will offer valuable insights into the advantages and constraints of each technique. The study intends to evaluate the practical consequences of the findings, providing recommendations for efficient and sustainable techniques in crop disease management in agriculture.

2. Literature Review

A comprehensive understanding of automated disease detection in agriculture necessitates a thorough examination of methodologies spanning various domains, including machine learning, deep learning, image processing, and statistical inference. Sammany et al. [1] delve into the application of Rough Sets for dimensionality reduction in neural network-based applications, demonstrating its effectiveness in diagnosing plant diseases and intrusion detection. By reducing input dimensions, Rough Sets streamline the computational complexity of neural network classifiers, enhancing classification accuracy. Their work

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underscores the adaptability and efficacy of Rough Sets across diverse domains, contributing to the advancement of feature selection methodologies. Nameirakpam Dhanachandra et al. [2] explore image segmentation using the K-means clustering algorithm and Subtractive clustering algorithm, integrated with partial stretching enhancement. Their methodology improves the accuracy of image segmentation by refining preprocessing techniques and incorporating innovative clustering methods. This study offers valuable insights into effective image segmentation methodologies, with potential applications in medical imaging and pattern recognition. K. He et al. [3] revolutionizes image recognition, enabling the training of deeper neural networks with higher accuracy.

Deep residual networks mitigate the vanishing gradient problem, achieving superior performance in image classification and object detection tasks. This seminal work influences advancements in neural network architectures, setting new standards for deep learning models' depth and efficiency. Ahmad et al. [6] address the challenge of optimizing plant disease detection models for resource-constrained devices. Their efficient approach combines Convolutional Neural Networks (CNNs) with transfer learning and class imbalance mitigation techniques, achieving high accuracy in disease classification tasks. Barbedo [8] emphasizes the importance of extensive and diverse datasets for the success of deep learning methods in plant pathology. Insufficient datasets hinder model generalization and accuracy, highlighting the urgent need for comprehensive image databases to advance automated disease identification systems. Barbedo [9] introduces a lesion-based method for plant disease identification, enhancing dataset variability and diagnostic accuracy. Although manual intervention is required, this method significantly improves illness classification performance, highlighting its potential in overcoming dataset limitations. Johannes et al. [10] propose an innovative image processing approach for early disease detection in agriculture, utilizing candidate hot-spot detection and statistical inference methods. Their methodology effectively detects disease hotspots in natural environments, enhancing integrated pest management systems' efficiency.

Islam et al. [11] present an automated method for plant disease diagnosis, combining image processing and machine learning techniques to achieve high classification accuracy. Their approach streamlines disease identification processes, contributing to food security and sustainable agriculture. Tiwari and Tarum [12] investigate the effectiveness of image processing techniques in detecting plant diseases, utilizing modified Support Vector Machine with Cuckoo Search optimization. Their autonomous approach accurately identifies diseased plant segments, simplifying agricultural diagnostics. Ramesh and Vydeki [13] propose an optimized deep neural network approach for disease classification in rice leaves, achieving high accuracy rates across multiple diseases. Their methodology demonstrates the potential of deep learning in advancing agricultural diagnostics. Singh et al. [14] highlight the importance of automated disease detection in agriculture, emphasizing the role of image segmentation and classification methodologies. Their algorithm offers a viable solution for optimizing disease identification processes, enhancing crop management techniques. Singh [15] presents an automated system for detecting diseases in sunflower leaves, utilizing Particle Swarm Optimization for image segmentation. The proposed method achieves high classification accuracy, improving sunflower crop management practices. These studies collectively contribute to advancing automated disease detection in agriculture, offering innovative methodologies and insights to enhance crop health management and promote sustainable agricultural practices.

3. METHODOLOGY

a. Overview

The adverse impacts of plant diseases on agricultural production present a significant concern, given their potentialthreat to food security if left untreated. Timely identificationof these diseases is crucial for effective prevention and control, playing a pivotal role in agricultural management anddecision-making processes. Image recognition technology emerges as a promising approach to address this challenge, aiming to develop an efficient method for early detection of leaf diseases and serve as the foundation for proactive agricultural strategies. The implementation of this technology, depicted in Figure 2, involves a

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systematic approach to discovering and categorizing leaf diseases through visual data analysis. This method not only accelerates the detection process but also enables a more thorough and precise evaluation of plant health. The objectiveis to provide agricultural experts with a tool that surpasses conventional disease identification methods, thereby enhancing their capabilities. By employing sophisticated image recognition techniques, the methodology can automateand improve the accuracy of disease identification, facilitating prompt intervention and reducing the risk of cropdamage. To delve into the intricacies of this approach, a strategic framework is introduced, enabling seamless integration of technology into agricultural management and enhancing the resilience and safety of the food production system.

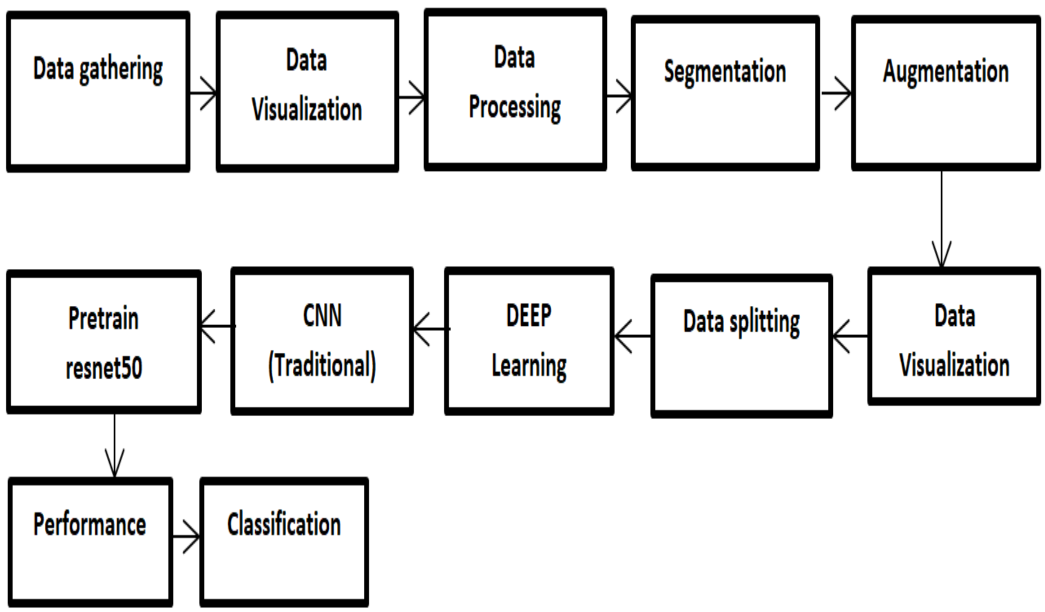

Figure 2: Flow diagram of the implementation process

b. Dataset Acquisition

The detection methodology for Corn or Maize Leaf Diseases relies on a comprehensive dataset obtained from reputable open platforms such as Kaggle and Mendeley.These platforms are renowned for their reliability and extensive collection of datasets, ensuring a broad representation of plant health conditions.

i. Data Structure

The dataset complies with the RGB image format, capturing crucial colour information essential for accurate disease detection. RGB images inherently provide a vast amount of visual data, allowing for the utilization of the complete range of colours observed in plant leaves. This format aligns with industry norms, facilitating seamless compatibility and integration into preexisting image processing pipelines.

ii. Data Preprocessing

Before engaging in model training, data preprocessing is essential to enhance the dataset for efficient learning. This includes activities such as standardizing image properties, adjusting dimensions, and improving image quality to maintain uniformity and minimize biases. Preprocessing plays a crucial role in improving the model's capacity to generalize across various instances of leaf illnesses, thereby strengthening its robust performance in real-world situations.

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c. Model Architecture

i. Models, Training and Validation

The methodology integrates CNN, ResNet, and U2Net models to handle segmentation and classification tasks in maize leaf disease detection. U2Net is sequentially applied for precise picture segmentation, prioritizing relevant characteristics identification and reducing background noise.Following segmentation, CNN and ResNet architectures perform classification, leveraging hierarchical information from segmented images to accurately identify and categorizediseases.

Training involves iterative epochs and loss calculations, enabling models to adjust parameters using labeled data. Validation serves as an impartial benchmark for assessing model generalization to new data. Selection of epochs and tracking of loss measures ensure continual improvement towards optimal performance. Evaluation metrics include heat maps, precision, recall, and F1-Score, providing insightsinto model focus, correctness in predictions, ability to identify positives, and overall resilience.

ii. Algorithm used

a. U^2 Net : The methodology employs a systematic five-step process for salient object detection using the U^2 Net model. It begins with image preprocessing, ensuring uniformity in input dimensions. The U^2 Net architecture, featuring an encoder, decoder, skip connections, nested U- structure, and dense connection blocks, capturessalient features effectively. Training involves labeled datasets and binary cross-entropy loss functions, optimized using Adam optimizer. Trainedmodels generate saliency maps highlighting salient regions, refined through post-processing techniqueslike thresholding and morphological operations for clarity.

b. Resnet 50: The construction of a powerful image classification model unfolds systematically. Input image dimensions are standardized, followed by theimplementation of initial convolutional layers with batch normalization and ReLU activation. Residualblocks, following ResNet-50 architecture, capture intricate hierarchical features while addressing the vanishing gradient problem. Fully connected layerswith global average pooling condense spatial dimensions and generate probability distributions. The model is compiled with appropriate loss functions and optimizers, trained on labelled datasets, and evaluated for generalization on separate validation or test sets. This comprehensiveapproach emphasizes careful design and consideration in constructing robust image classification models.

4. RESULTS AND DISCUSSION

In this particular scenario, the research utilizes a total of four diverse datasets, each focusing on specific types of plantdiseases. These datasets encompass a wide range of plant species and diseases, allowing for comprehensive analysis and exploration of disease detection methodologies across different agricultural contexts. The datasets include information on diseases affecting Corn or Maize Leaves, Large Wheat Diseases, Tomato Leaf Diseases, and Cassava Leaf Diseases. By incorporating such varied datasets, the study aims to provide a holistic understanding of disease detection techniques applicable to different crops, thereby contributing to the development of robust and versatile agricultural disease management strategies.

a. Corn or Maze leaf Disease

Corn, often known as maize, is a globally cultivatedagricultural crop produced in large quantities. In addition, it serves as the fundamental ingredient for various other goods,including cooking oil, starch, flour, sugar, biofuel, alcohol, and animal feed. Corn shows adaptability to diverse environmental conditions and is regarded as a crucial crop because to its extensive genetic variety and significant production capacity, comparable to that of rice and wheat. In2020, the worldwide corn production amounted to 1.15 billion tons. The plant is inherently susceptible to numerous diseases that can affect different sections of the plant, such asthe leaves, trunk, and fruit, at all stages of growth. This directly affects the corn harvest output and might result in significant financial losses. Insufficient agricultural yield of essential crops like maize can have

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worldwide ramifications, including food scarcity, malnutrition, and potentially widespread famine. The most hazardous illnesses are the diseases that infect the leaves of corn plants during their growth cycle. Hence, this work considers three common leaf diseases:

- Common Rust.
- Grey Leaf spot.
- Northern leaf.

i. Common Rust: The fungal pathogen Puccinia sorghiis accountable for the development of common rust, an annual phenomenon observed during each growing season, albeit rarely a concern in hybrid corn. Rust pustules typically emerge in late June. Initial indications of common rust manifest as chlorotic particles on the leaf surface, progressing into powdery, brick-red pustules when the spores penetrate the leaf surface. These pustules, measuring approximately 1/8 inch in length, are oblong or elongated and can appear sparsely distributed or clustered together. Surrounding leaf tissue may exhibit yellowing or necrosis, leading to the formation of lesions of dead tissue. In severe cases, these lesions may extend throughout the leaf, resulting in the death of entire leaves. Mature pustules undergo a colour change to black, emerging through the leaf surface, and can also infect husks, leaf sheaths, and stalks. These features delineate the progression and impact of common rust on cornplants.

ii. Gray leaf spot: Gray leaf spot, attributed to the fungus Cercospora zeae-maydis, recurs consistently each growing season and can result in significant financial losses under conducive disease growth conditions. Key factors include the following: Initialsymptoms manifest on lower leaves approximately two to three weeks before tasseling, with lesions elongating up to 2 inches in length and adopting a narrow, rectangular shape with a light tan hue. Theselesions may progress to a Gray coloration and are often delimited by leaf veins, though they can merge, ultimately leading to the demise of entire leaves.

iii. Northern leaf blight: The fungus Setosphaeria turcicais the primary cause of Northern corn leaf blight (NCLB), presenting several characteristic features. Typically, symptoms first emerge on lower leaves, with elongated lesions measuring 1 to 6 inches in length and exhibiting an elliptical shape. Initially appearing gray-green, these lesions later transition toa pale gray or tan color. Under humid conditions, dark gray spores develop, primarily on the undersideof leaves, resulting in lesions with a "dirty" gray appearance. Severely affected plants may experiencecomplete leaf death, making it challenging to observeindividual lesions. Additionally, lesions may also form on the exterior surface of ears, although the kernels themselves remain unaffected. Hybrids carrying the Ht gene for fungal resistance may display smaller lesions that are chlorotic and can progress into linear streaks, with spore production being rare. To facilitate image segmentation, raw images undergo the creation of mask images through simple thresholding applied individually to each specified category. These mask images are then employed alongside the raw images for image segmentation utilizing the U2Net Model.

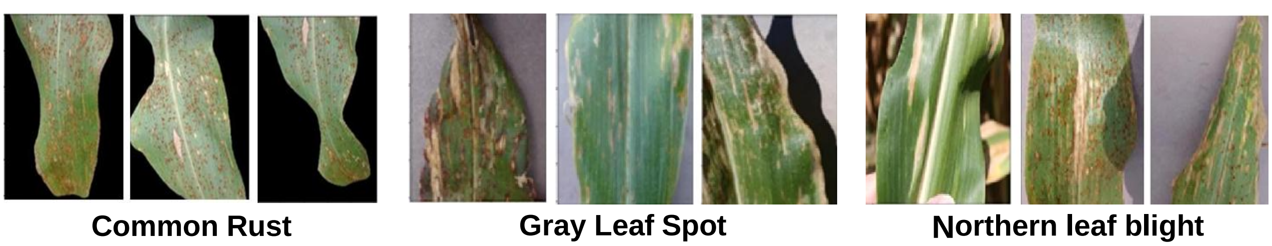

Figure 3: Visual Representation of Common Rust, Gray Leaf Spot & northern leaf blight

Table 1: Precision, Recall, F1-Score of Corn or Maze leaf Disease

DOI: https://doi.org/10.71058/jodac.v9i4004

Diseases	Precision	Recall	f1-score
Blight	0.92	0.93	0.93
Common Rust	0.97	0.98	0.97
Gray Leaf Spot	0.90	0.85	0.88
Healthy	1.00	1.00	1.00

The table 1 presents Precision, recall, and F1-score metrics for four classes: Blight, Common Rust, Gray Leaf Spot, and Healthy. It also indicates the overall accuracy of theclassification model. Notably, Healthy exhibits perfect precision, recall, and F1-score, indicating flawless classification. Other classes also demonstrate high performance metrics, with Common Rust showing particularly strong precision and recall. The overall accuracyof the model is 95%.

b. Large Wheat Disease

Agriculture played a crucial role in the economy during the medieval era, synchronizing with the beginnings of the industrial revolution. Wheat, a vital cereal grain, has becomeessential for satisfying nutritional requirements and maintaining physiological processes. Nevertheless, the agricultural productivity encountered substantial obstacles asa result of prevalent diseases, impeding the widespread availability of this particular crop. Due to the prevalence of illiteracy among agricultural practitioners, the implementation of timely preventive measures became challenging, leading to a decline in wheat production. The early detection of wheat diseases presented additional difficulties due to the numerous environmental factors and the low literacy rate among workers. Numerous diagnostic models have been put forth in response, with the objective oftackling diseases such as Crown and Root Rot, Leaf Rust, and Wheat Loose Smut represented in figure 4,5, and 6 respectivily. This study aims to investigate common leaf diseases in order to develop efficient diagnostic approaches.

Figure 4: Crown and Root Rot

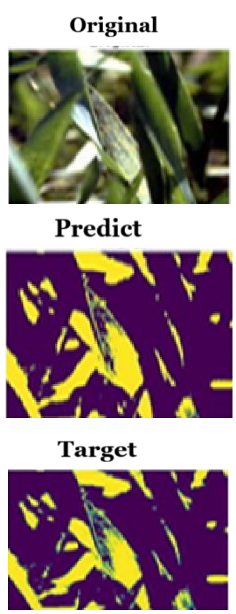

Figure 5: Leaf Rust

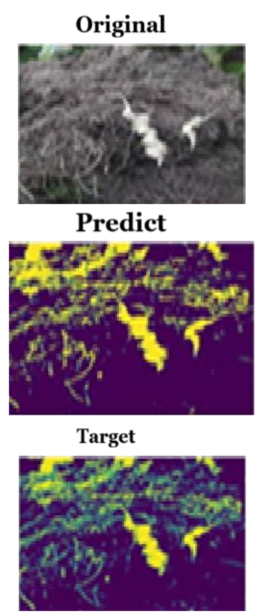

Figure 6 (i): Healty Wheat

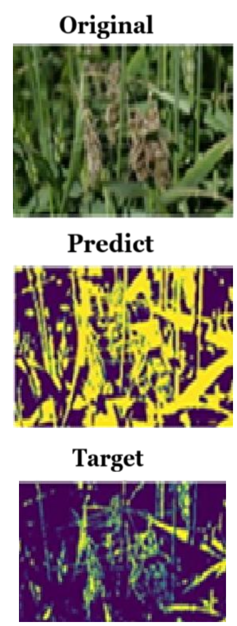

Figure 6 (ii): Wheat Loose Smut

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Following the generation of raw images, mask images are created through a straightforward thresholding process, establishing masks independently for each image within specified categories. Subsequently, the raw images and corresponding mask images are utilized for image segmentation employing the U2Net Model. This segmentation process facilitates the delineation and isolation of relevant features within the images, enabling precise analysis and identification of targeted areas of interest.

Table 2: Precision, Recall, F1-Score of Large Wheat Disease

Disease	Precision	Recall	Fl-Score
Crown and Root Rot	0.97	0.76	0.85
Healthy Wheat	0.79	0.93	0.85
Leaf Rust	0.91	0.96	0.94
Wheat Loose Smut	0.87	0.86	0.87

The wheat disease classification model achieved varying performance metrics across different disease categories. Crown and Root Rot showed high precision (0.97) but lowerrecall (0.76), resulting in an F1-score of 0.85. Healthy Wheathad lower precision (0.79) but higher recall (0.93), yielding the same F1-score. Leaf Rust demonstrated balancedprecision and recall (0.91 and 0.96, respectively), with an F1-score of 0.94. Wheat Loose Smut achieved an F1-score of 0.87, with precision and recall both at 0.87 and 0.86, respectively as shown in Table 2. Overall accuracy stood at 0.89, indicating the model's effectiveness in distinguishing between wheat disease categories.

c. Tomato Leaf Disease

In major agricultural economies, over 65% of the population is involved in farming, with tomatoes being a key crop grown by 9 out of 10 farmers. In India alone, tomatoes are cultivated over 350,000 hectares, yielding about 5.3 million tons. To obtain flavourful tomatoes, many gardeners cultivate them in their own gardens. However, frequently, those farmers and gardeners do not get comprehensive advancement in the growth of the produce. This enhances the probability of contracting illnesses. Diseased plants account for 10 to 30% of the total crop loss. Hence, this work considers common leaf diseases:Target Spot, Mosaic Virus, Yellow Leaf Curl Virus, Bacterial Spot, Early Blight, Late Blight ,Leaf Mold and Spider mites represented in figure 7.

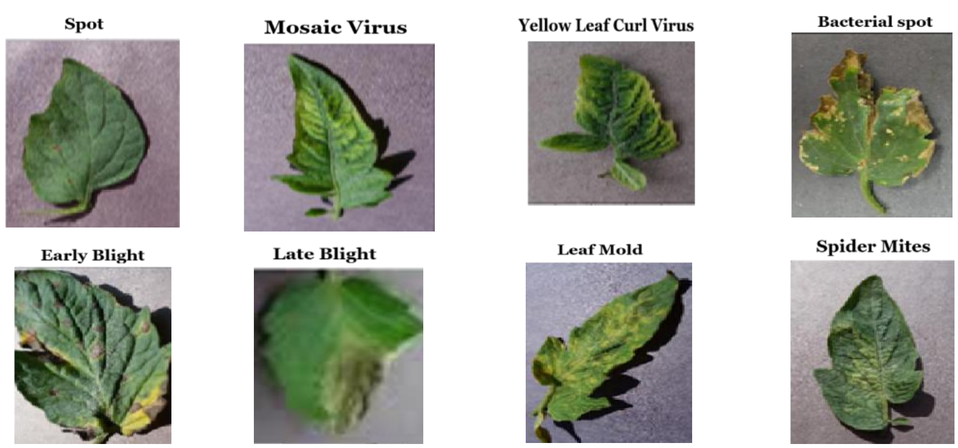

Figure 7: Raw images of Tomato Leaf disease

Next, mask images were generated from the raw images by applying a simple threshold. Each image was processed individually and independently within specified categories. Subsequently, the raw

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images along with their corresponding mask images were utilized for image segmentation for the predicted and targeted images represented in figure 8 using U2Net Model.

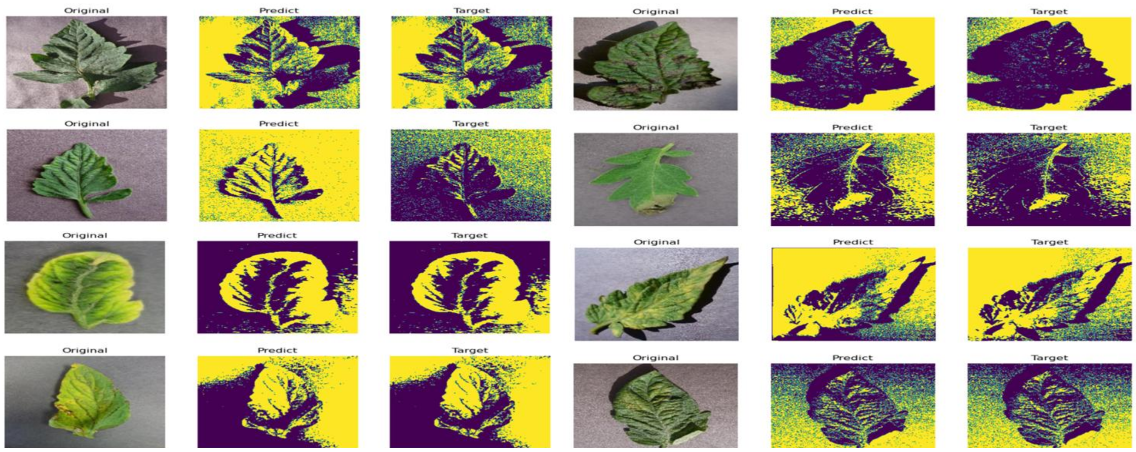

Figure 8: Image segmentation using U2Net Model

The table 3 displays precision, recall, F1-score, and accuracy metrics for different plant diseases and a healthy category. The model exhibits high precision and recall scoresfor most diseases, indicating accurate detection. However, diseases like Early Blight and Sellowleaf Curl Virus show lower recall scores, suggesting potential misclassifications. The accuracy metric confirms the overall effectiveness of themodel in distinguishing between healthy and diseased plants,achieving an accuracy of 94%.

Table 3: Precision, Recall, F1-Score of Tomato Leaf Disease

Diseases	Precision	Recall	F1-Score
Bacterial Spot	0.97	0.97	0.97
Early Blight	1.00	0.65	0.79
Late Blight	0.94	0.98	0.96
Leaf Mold	0.98	0.97	0.98
Spider mites Two spotted spider mite	0.90	0.99	0.95
Target Spot	1.00	0.93	0.96
Yellow leaf Curl Virus	0.99	0.98	0.83
Mosaic Virus	0.96	0.99	0.99
Healthy	1.00	0.81	0.97

d. Cassava Leaf Disease

Cassava, scientifically termed Manihot esculenta Crantz,plays a crucial role as a staple food crop in sub-Saharan Africa, where both its tubers and foliage are vital sources of nutrition. However, the plant faces significant threats from various infections, particularly less familiar viral strains like Cassava Mosaic Disease (CMD) and Cassava Brown Streak Disease (CBB), which have historically caused widespread devastation in regions like Uganda and Tanzania. Theseinfections, characterized by symptoms such as leaf yellowingand root decay, pose substantial risks to cassava cultivation and food security in the region. To address these challenges, there is a pressing need for enhanced automated methods for the rapid identification and prevention of cassava diseases.

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Traditional diagnostic approaches relying on human expertise are often labour-intensive and inefficient, especiallyfor promptly detecting cassava infections. Our study introduces a novel approach that leverages Convolutional Neural Networks (CNNs) trained from scratch with an imbalanced dataset to classify five common leaf diseases affecting cassava: CMD, Cassava Green Mottle (CGM), CBSD, Yellow Leaf Curl Virus, and Cassava Bacterial Blight(CBB). This innovative approach aims to improve disease detection and management strategies in cassava cultivation, contributing to sustainable food production and agricultural resilience in sub-Saharan Africa.

After generating mask images from the raw images through a straightforward thresholding process, individual masks are created independently for each image within predefined categories. These masks, representing specific features or areas of interest, serve as crucial inputs for image segmentation using the U2Net Model. By combining the raw images with their corresponding mask images, the U2Net Model can accurately segment and identify relevant objects or regions within the images, facilitating tasks such as diseasedetection or feature extraction in various applications. This approach enables efficient and precise analysis of image data represented in figure 9,enhancing the capabilities of computer vision systems in diverse fields such as agriculture, medicine, and environmental monitoring.

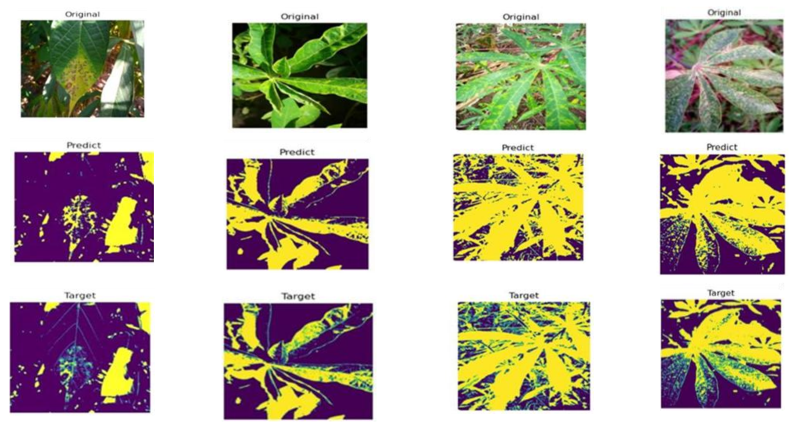

Figure 9: Analysis of Cassava Leaf Disease

Table 4: Precision, Recall, F1-Score of Cassava Leaf Disease

Diseases	Precision	Recall	F1-Score
Cassava BacterialBlight (CBB)	0.74	0.69	0.71
Cassava Brown Streak Disease (CBSD)	0.89	0.47	0.61
Cassava Green Mottle(CGM)	0.66	0.75	0.70
Cassava NosaicDisease (CMD)	0.80	0.80	0.80
Healthy	0.52	0.73	0.61

After completing the data augmentation process and dividing the dataset into training and testing sets, we employthe ResNet50 deep learning model, pre-trained using the PyTorch library, for classification purposes. Due to the highly imbalanced nature of the data, only a subset of the data is usedfor training, limited to 10 epochs. Despite this limitation, themodel achieves a training accuracy of 75% and a testing accuracy of 69% as shown in Table 4. This indicates that themodel performs reasonably well in classifying the data, considering the challenges posed by the imbalanced dataset.

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Table 5 presents a comparison of different plant diseases detection models, focusing on the ResNet50-U2Net combination. The table outlines the models used, algorithms applied, and corresponding training and testing accuracies. Across various diseases like Corn/Maize Leaf, Large Wheat, Tomato Leaf, and Cassava Leaf, the ResNet50-U2Net combination consistently demonstrates high performance, achieving notable accuracies in both training and testing phases.

Table 5: Comparison Table of Different Plants

Diseases	Model Used	Algorithm Used	Training Accuracy	Testing Accuracy
Corn/Maize Leaf	ResNet 50	U2Net	97%	95%
Large Wheat Disease	ResNet 50	U2Net	90%	87%
Tomato Leaf Disease	ResNet 50	U2Net	98%	93%
Cassava Leaf Disease	ResNet 50	U2Net	75%	69%

5. CONCLUSION AND FUTURE SCOPE

The investigation of agricultural computer vision for disease classification has yielded promising results for vital crops like maize, wheat, tomatoes, and cassava. Analysing diverse datasets revealed insights into disease patterns and complexities, notably in Corn or Maize Leaf Disease, where precise mask images and U2Net Model segmentation identified common rust, grey leaf spot, and northern leaf blight with 97% Training Accuracy and 95% Testing Accuracy. Similarly, the examination of Large Wheat Disease achieved commendable accuracies of 90% and 87%, highlighting the framework's potential in precise disease identification. Tomato Leaf Disease analysis demonstrated exceptional performance with 98% Training Accuracy and 93% Testing Accuracy, showcasing the method's effectiveness in identifying various tomato diseases. Despite challenges from imbalanced datasets, the Cassava Leaf Disease analysis showed promise with 75% Training Accuracy and 69% testing accuracy, emphasizing the need for further investigation. Overall, the research underscores the efficacy of a comprehensive framework combining image processing and deep learning models while identifying areas for improvement, particularly in managing imbalanced datasets. This study contributes significantly to advancing agricultural computer vision applications, laying the groundwork for enhancing crop health and sustainability.

The study of agricultural artificial intelligence for the classification of maize diseases presents opportunities for future progress. Potential areas for exploration include the integration of advanced deep learning architectures such as Vision Transformer (ViT) and the utilization of ensemble learning methodologies to enhance precision. Innovative techniques for data augmentation, the utilization of edge computing and Internet of Things (IoT) devices in real-time surveillance systems, and the incorporation of multimodal data present encouraging opportunities for improving disease detection and categorization. The aforementioned advancements underscore the dynamic nature of agricultural computer vision and its capacity to transform the field of crop health management.

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Author Contributions

All authors have equally contributed.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the study of this article.

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References

[1] M. Sammany and T. Medhat, "Dimensionality Reduction Using Rough Set Approach for Two Neural Networks-Based Applications," in Intelligent Systems Paradigms. RSEISP 2007, vol. 4585, Berlin, Heidelberg: Springer, 2007, pp. 779-789. [Online]. Available: https://doi.org/10.1007/978-3-540-73451-2_67.

[2] N. Dhanachandra, K. Manglem, and Y. J. Chanu, "Image Segmentation Using K-means Clustering Algorithm and Subtractive Clustering Algorithm," Procedia Computer Science, vol. 54, pp. 764-771, 2015. [Online]. Available: https://doi.org/10.1016/j.procs.2015.06.090.

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proc. 2016 IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 770-778. [Online]. Available: https://doi.org/10.1109/CVPR.2016.90.

[4] M. Abadi et al., "TensorFlow: A System for Large-Scale Machine Learning," in USENIX Symposium on Operating Systems Design and Implementation, 2016.

[5] T.-Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie, "Feature Pyramid Networks for Object Detection," in Proc. 2017 IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 936-944. [Online]. Available: https://doi.org/10.1109/CVPR.2017.106.

[6] M. Ahmad, M. Abdullah, H. Moon, and D. Han, "Plant Disease Detection in Imbalanced Datasets Using Efficient Convolutional Neural Networks with Stepwise Transfer Learning," IEEE Access, vol. 9, pp. 140565-140580, 2021. [Online]. Available: https://doi.org/10.1109/ACCESS.2021.3119655.

[7] G. N. Agrios, Plant Pathology, 5th ed., Burlington, MA, USA: Elsevier Academic Press, 2005, pp. 79–103.

[8] J. G. A. Barbedo, "Impact of Dataset Size and Variety on the Effectiveness of Deep Learning and Transfer Learning for Plant Disease Classification," Computers and Electronics in Agriculture, vol. 153, pp. 46–53, 2018. [Online]. Available: https://doi.org/10.1016/j.compag.2018.07.007.

[9] J. G. A. Barbedo, "Plant Disease Identification from Individual Lesions and Spots Using Deep Learning," Biosystems Engineering, vol. 180, pp. 96–107, 2019.

[10] A. Johannes et al., "Automatic Plant Disease Diagnosis Using Mobile Capture Devices, Applied on a Wheat Use Case," Computers and Electronics in Agriculture, vol. 138, pp. 200–209, 2017.

[11] M. Islam, A. Dinh, K. Wahid, and P. Bhowmik, "Detection of Potato Diseases Using Image Segmentation and Multiclass Support Vector Machine," in Proc. Can. Conf. Electrical and Computer Engineering, 2017, pp. 8–11.

[12] V. M. Tiwari and G. Tarum, "Plant Leaf Disease Analysis Using Image Processing Technique with Modified SVM-CS Classifier," Int. J. Eng. Manag. Technol., vol. 5, pp. 11–17, 2017.

[13] S. Ramesh and D. Vydeki, "Recognition and Classification of Paddy Leaf Diseases Using Optimized Deep Neural Network with Jaya Algorithm," Information Processing in Agriculture, 2019.

[14] V. Singh, V. Varsha, and A. K. Misra, "Detection of Unhealthy Region of Plant Leaves Using Image Processing and Genetic Algorithm," in Conf. Proceeding-2015 Int. Conf. Adv. Comput. Eng. Appl. (ICACEA), 2015, pp. 1028–1032.

[15] V. Singh, "Sunflower Leaf Diseases Detection Using Image Segmentation Based on Particle Swarm Optimization," Artificial Intelligence in Agriculture, 2019.

[16] S. S. Chouhan, A. Kaul, U. P. Singh, and S. Jain, "Bacterial Foraging Optimization Based Radial Basis Function Neural Network (BRBFNN) for Identification and Classification of Plant Leaf Diseases: An Automatic Approach Towards Plant Pathology," IEEE Access, vol. 6, pp. 8852–8863, 2018.

[17] X. E. Pantazi, D. Moshou, and A. A. Tamouridou, "Automated Leaf Disease Detection in Different Crop Species Through Image Features Analysis and One Class Classifiers," Computers and Electronics in Agriculture, 2019. [Online]. Available: https://doi.org/10.1016/j.compag.2018.11.005.

[18] Y. Lecun, Y. Bengio, and G. Hinton, "Deep Learning," Nature, vol. 521, pp. 436–444, 2015.

[19] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep Neural Networks-Based Recognition of Plant Diseases by Leaf Image Classification," Computational Intelligence and Neuroscience, 2016.

[20] S. P. Mohanty, D. P. Hughes, and M. Salathe, "Using Deep Learning for Image-Based Plant Disease Detection," Frontiers in Plant Science, vol. 7 pp. 1–10, 2016.