Deep Learning Based Multi Crop Disease Detection System

Gul Munir[1], M. Ahsan Ansari[1*], Sammer Zai[1], Irfan Bhacho[1]
[1]Department of Computer Systems Engineering, Mehran UET, Jamshoro, Pakistan
***Correspondence:** M. Ahsan Ansari, ahsan.ansari@faculty.muet.edu.pk

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This research explores the integration of deep learning, computer vision, and edge computing to revolutionize crop disease detection. In response to the pressing need for prompt and accurate disease identification, this work leverages the capabilities of edge computing devices deployed within agricultural fields. Real-time data processing at the edge facilitates quick disease classification across various crops, enabling timely interventions. At the heart of the methodology lies a fine-tuned ResNet50 deep learning model, specifically chosen for its proficiency in handling complex visual data. Trained on a specialized dataset derived from the ImageNet database, the model exhibits promising accuracy rates in preliminary testing. Integrating edge computing into precision agriculture, this research presents a significant advancement toward sustainable agricultural practices. By empowering farmers with early detection and timely interventions, this endeavor equips agricultural communities with the knowledge and tools necessary to safeguard their crops, ensuring both food security and economic stability.

Keywords: Deep learning; Precision architecture; Computer Vision; Crop disease detection; Sustainable agriculture.

Introduction:

Agriculture forms the backbone of the global economy, providing food and sustenance for billions of people worldwide. However, this vital sector faces constant threats, including the devastating impact of plant diseases. These diseases inflict significant crop losses, leading to economic hardships and food insecurity for millions. Each year, crop diseases result in substantial economic losses worldwide estimated at around $220 billion. This figure excludes the additional $70 billion in costs from other pests, such as invasive insects. These financial impacts affect major crops like bananas, cucumbers, chilies, wheat, and rice [1]. For example, in rice, significant diseases such as bacterial blight, rice blast, and sheath blight cause considerable yield reductions. These diseases contribute extensively to the global economic burden, with annual losses reaching billions of dollars. The situation is further worsened by intensive farming practices and global trade, which facilitate the spread of pathogens [2].

This problem has been exacerbated by factors such as climate change, globalization, and intensive agricultural practices. To address this challenge and ensure food security, it is imperative to develop novel systems that assist farmers and businesses in mitigating losses and maximizing gains. Early and accurate detection of plant diseases is crucial for mitigating their impact and minimizing damage. Traditional methods, primarily relying on visual inspection by farmers, often prove insufficient. Such approaches are time-consuming, labor-intensive, and susceptible to human error, particularly in the early stages of infection when symptoms are subtle and easily overlooked. Additionally, accurately identifying diseases across numerous crops adds another layer of complexity, as each crop presents unique vulnerabilities and disease symptoms

Recent advancements in machine learning and artificial intelligence (AI) have paved the way for the development of automated multi-crop disease detection systems. These systems leverage deep learning algorithms to analyze images of plant leaves and stems, enabling accurate identification and classification of various diseases across diverse crops. This revolutionary technology holds immense promise to significantly improve upon traditional methods by offering an efficient and automated approach to multi-crop disease detection. By empowering farmers to identify and control diseases early on, multi-crop disease detection systems offer the potential to reduce crop losses, optimize yield, and ultimately enhance global food security. This rapidly evolving field is poised to witness the development of cutting-edge technologies and applications readily adaptable by stakeholders within the farming landscape.

To address these challenges, the development of an automated multi-crop disease detection system is crucial. Leveraging advancements in machine learning and image processing, this system can significantly improve disease management in agriculture by:

1. Enabling early and accurate disease identification across diverse crops.
2. Empowering farmers with timely insights to implement effective interventions.
3. Reducing reliance on expert knowledge and labor, making disease detection more accessible.
4. Improving crop yields and farmer livelihoods

Novelty and Objectives of Study:

Automated multi-crop disease detection systems powered by machine learning and deep learning algorithms offer a transformative solution. These systems hold immense potential to revolutionize plant disease management by offering:

- **Speed and Efficiency:** Such Systems will process images rapidly, automatically analyze them, and predict the disease with remarkable efficiency, freeing farmers from tedious manual inspection.
- **Accuracy and Reliability:** By leveraging powerful machine learning algorithms, the model can be trained to achieve high accuracy in disease prediction. Farmers can rely on

the system's reliable results to make informed decisions about crop management and disease control.

The Key objectives of this study are:

1. Collect a comprehensive dataset of leaf images representing various crops and disease conditions from diverse sources.
2. Preprocess the dataset for standardization of image size, format, and quality to enhance algorithm training and evaluation efficiency.
3. Design and implement a deep learning algorithm based on the ResNet50 architecture for accurate disease identification across diverse crops utilizing leaf images.
4. Optimize the algorithm for performance and efficiency, ensuring real-time image processing and minimal resource utilization on mobile devices.

Literature Review:

Recent research highlights the potential of advanced technologies, such as deep learning and image processing, for accurate and accessible multi-crop disease detection.

Deep learning models achieve high accuracy in disease identification, as demonstrated by InceptionResNetV2 for okra (98%) [3]. PlantifyAI app uses deep learning algorithms to identify crop diseases with 95.7% accuracy [4]. CNNs effectively detect diseases across various crops, with ResNet-152 and InceptionV3 variants achieving 98.81% for corn and 97.48% for rice [5] [6].

Mobile applications offer user-friendly interfaces and real-time information for disease management, as shown by models for cucumber, guava, and other crops (98.27% accuracy) [7]. Moreover, the research addresses challenges like messy images (U-Net segmentation for tomato plants, 98.12% accuracy) [8] and real-world environments (YOLOv5 for chili crops, 75.64% accuracy) [7] [9]. Future research should focus on optimizing models for diverse datasets, real-world conditions, and integration with other agricultural technologies for broader accessibility and impact [10] [11] [12] [13].

Material and Methods:

This section provides a comprehensive overview of the system design and methodology, including the following key components:

Data Acquisition:

The very first challenge in this research was to acquire a comprehensive dataset of leaf images representing various crops and disease conditions from diverse sources. A diverse dataset of crop disease images was acquired from various sources, including the internet, open-access repositories, and agricultural institutions. The primary source of the data was an online open-access repository known as Kaggle (Plant Village Dataset). This dataset consists of 70,000 high-quality images of diseased and healthy plant leaves from 9 different species. Each species has 3 data splits (train, test, and validation), with consistent categories across all splits. This dataset is ideal for machine learning researchers and practitioners working on plant disease detection and classification, as well as for agricultural experts seeking to improve plant health and crop yields. The dataset is unique in its diversity, covering a wide range of plant species, diseases, and growth stages. Table 1 shows the details of crop images gathered from various sources.

Data Preprocessing:

The dataset was meticulously pre-processed to ensure uniformity and quality. A suite of data augmentation techniques was used to augment the dataset and strengthen the model's adaptability. By rotating, flipping, and shifting the images, a spectrum of variation was introduced to the original dataset, broadening the inputs for the model. As a result of this diversification process, the model was able to generalize and classify unseen samples more efficiently. To achieve the best balance between variability and preservation of essential features, augmentation parameters were strategically chosen. These parameters included:

- **Rescaling:** Image rescaling ensures uniform pixel values and speeds up computation by rescaling the images to [0,1].

Table 1. Dataset Description

S.No	Crop Name	# of diseases	Total Images in Original Datasets	Total Images after augmentation	Training – Testing split	
					Training images	Validation images
1	Banana	4	586	937	777	160
2	Chillies	5	227	459	400	59
3	Cotton	6	1537	2637	2400	237
4	Cucumber	7	4678	6729	5600	1129
5	Rice	4	1845	3355	2684	671
6	Sunflower	4	125	355	253	102
7	Sugarcane	3	196	459	350	109
8	Tomato	9	14876	27713	21985	5728
Total		42	24070	42644	34449	8195

- **Shear Range:** To simulate the distortions of real-world images, a shear range of 0.2 was applied to the images, introducing controlled deformations.
- **Zoom Range:** By employing a zoom range of 0.2, the model can learn from images at varying scales, mimicking natural fluctuations in object proximity.

Horizontal Flip: Using horizontal flips, the model was provided with mirrored perspectives to learn from. Figure 1 shows a diagram showing steps from data acquisition to data pre-processing. Figure 2 shows the original image and pre-processed image.

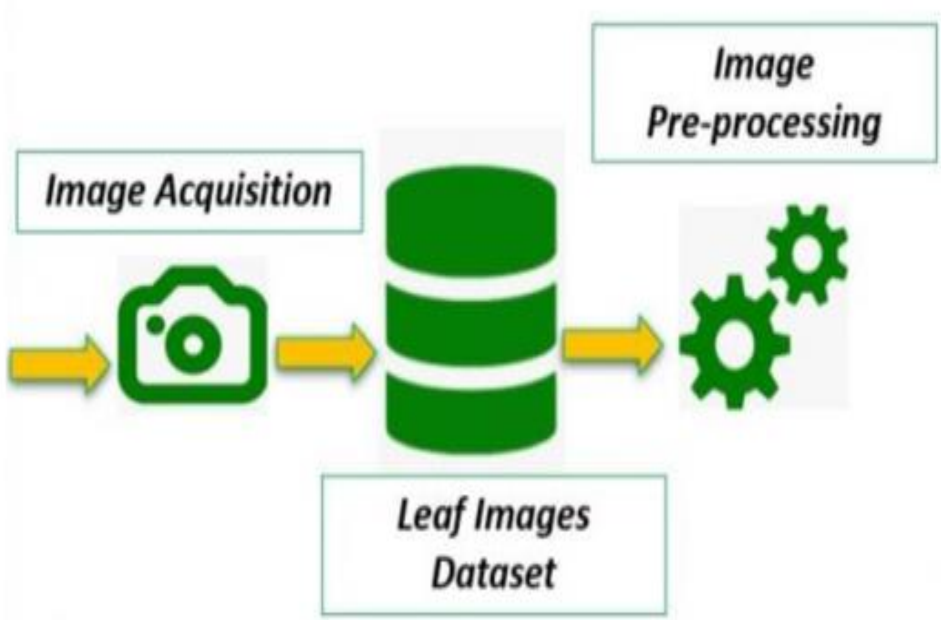

Figure 1. Diagram from data acquisition to data preprocessing. Reprinted from "ConvPlant-Net: a convolutional neural network-based architecture for leaf disease detection in smart agriculture national conference on communication," by S. D. Deb, R. K. Jha, S. Kumar, 2023, (Presentation) [14].

(a) **(b)**

Figure 2. (a) Original Image (b) Preprocessed Image

Data Balancing:

This process involved meticulously reviewing the dataset to mitigate issues related to class imbalance, identifying and eliminating instances of blurred or confusing images, and ensuring that high-quality samples were included in the study. A significant amount of attention was given during the training process to maintaining a proportional representation of healthy and diseased samples. This approach allowed the model to learn from a comprehensive and well-balanced set of examples, thus avoiding any undue bias toward the class with the most frequent occurrences. In this way, robust and reliable disease detection capabilities were achieved.

Model Description:

The ResNet50 model was selected based on its architectural prowess, pre-trained weights, and demonstrated performance in agricultural applications. In the field of deep learning architectures, ResNet50 is renowned for its exceptional ability to classify images. As we know, the devil lies in the details when it comes to agriculture, particularly plant disease detection. Subtle variations, nuanced patterns, and distinct features are often the key to distinguishing healthy plants from diseased ones. Due to ResNet50's ability to capture intricate details, it can detect even the slightest signs of plant diseases. This level of precision is critical to ensuring accurate disease detection. Furthermore, with its deep architecture, ResNet50 is distinguished from other models. As a result of this depth, the model is capable of learning hierarchical features from images, which is important for the detection of plant diseases. A comprehensive spectrum of features can be extracted by ResNet50 through its deep layers, ranging from simple textures to intricate structures. Feature learning through hierarchical classification is invaluable in predicting plant health accurately. ResNet50 model was fine-tuned on the crop disease dataset using a rigorous training and validation process. The following parameters were used during the training and validation process.

1. **Learning Rate:** This controls the size of the steps taken during gradient descent optimization. It likely had to be fine-tuned for optimal convergence and generalization.
2. **Momentum:** This helps the optimizer avoid getting stuck in local minima and smooths the learning process. Its value was likely adjusted for optimal performance.

3. **Weight Decay:** This helps prevent overfitting by penalizing large weights. Its value was likely adjusted to balance model complexity and generalization.
4. **Optimizer:** The specific optimizer used, such as Adam or SGD, may have been chosen based on its performance on the crop disease dataset.
5. **Loss Function:** The loss function used to evaluate the model's performance, likely cross-entropy, could have been adjusted to prioritize specific aspects of the predictions.

Hyperparameters were optimized to achieve optimal model convergence and generalization. The ResNet50 model was fine-tuned based on the following parameters:

6. **Last Few Layers:** The final fully connected layers of ResNet50 are typically replaced with new layers specific to the task at hand, in this case, crop disease classification. The number of neurons and activation functions in these layers were likely fine-tuned.
7. **Dropout Rates:** Dropout layers introduce randomness to prevent overfitting, and their rates could have been adjusted for optimal performance.
8. **Batch Size:** The batch size affects the speed and stability of training. It likely had to be fine-tuned for the specific hardware resources available.

The trained model was rigorously evaluated using various metrics, including accuracy, precision, recall, F1-score, confusion matrix, ROC curve, and validation on unseen data.

Edge Computing Implementation

The proposed framework leverages a multi-layered architecture with four fundamental components: the sensing layer, the edge computing layer, the network layer, and the application layer. Figure 3 shows the data sensing framework for the crop field with the utilization of edge computing.

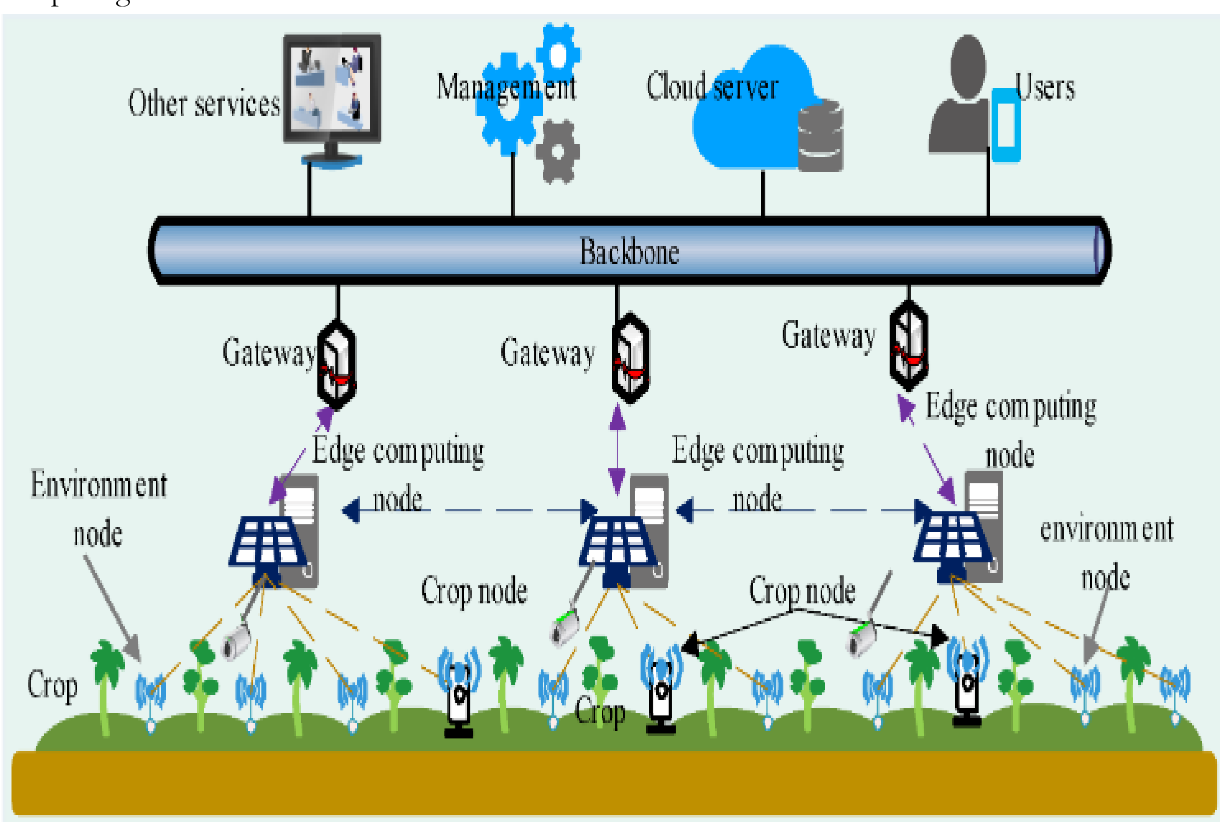

Figure 3. The data sensing framework for the entire crop lifecycle is based on IoT and edge computing. Reprinted from "Edge Computing driven data sensing strategy in the entire crop lifecycle for smart agricultural", by R. Zheng, X. Li, 2021, Sensors 21(22) 7502, page no. 4, MDPI [15].

Sensing Layer:

At the core of this layer are numerous nodes equipped with diverse sensors, power units, memory, micro-processing capabilities, and wireless communication modules. These nodes fulfill distinct functions, categorized into crop monitoring nodes and environmental sensing nodes to observe both crop growth and environmental parameters, respectively.

Edge Computing Layer:

This layer encompasses multiple nodes designed with rechargeable units for enhanced operational continuity. These nodes process and analyze data locally, enabling real-time decision-making without relying solely on the cloud.

Network Layer:

Serving as the connecting bridge, this layer incorporates wired and wireless media, diverse communication protocols, and various gateway and routing equipment. It facilitates seamless communication among all devices and layers within the system.

Application Layer:

Centered on the cloud server, this layer hosts agricultural users and terminals, intelligent monitoring and control systems, and other crucial applications and services. It provides users with insights and control functionalities based on the collected data and analysis.

Clustered Based Topology:

Within the sensing layer, a cluster-based topology optimizes network efficiency. Each cluster operates under the supervision of an edge computing node acting as a cluster head, managing the network resources within its domain.

Working Principle:

The edge computing system operates through a systematic series of steps for efficient data acquisition and analysis: The cloud server establishes a crop expert system based on historical data. This system defines classification standards for various crop growth stages and evaluates priority indicators for each stage. It also identifies key environmental factors aligned with different growth stages by analyzing their correlation with primary crop growth indexes. The edge computing node retrieves operational parameters and instructions from the cloud server. It coordinates crop monitoring nodes to collect specific crop-related parameters periodically throughout distinct growth stages. Utilizing an artificial neural network, the edge computing node identifies the current growth stage and retrieves key crop growth indicators. Additionally, it calculates the correlation between environmental parameters and these growth indicators.

Based on time constraints and specific criteria, the edge computing node selects relevant feature parameters for crops and environmental factors. It then defines a set of sensing nodes with suitable coverage and participation numbers. These selected nodes are activated to initiate parameter sensing and collect crucial data for analysis.

Activated sensing nodes gather parameter data and transmit it to both the edge computing node and the cloud server. This collected data undergoes thorough analysis and processing to derive insights into crop growth stages, key indicators, and the relationship between environmental factors and crop health.

Result and Discussion:

This section outlines the results achieved and insights gained during the study, which leveraged various tools and technologies. Python served as the primary programming language, employing libraries like Scikit-learn, TensorFlow, and Keras for data manipulation, machine learning, and deep learning. Model development relied on TensorFlow's deep learning capabilities and Keras' high-level API for rapid prototyping. Image processing tasks were handled by OpenCV and PIL/Pillow for pre-processing and manipulation. Collaborative version control and development were achieved through Git and GitHub.

In the early stages of this research, various models such as InceptionV3, Convolutional Neural Networks (CNNs), Xception, and Support Vector Machines (SVMs), were explored along with their strengths and limitations for agricultural disease detection. The evaluation of initial models showed promising results however their performance was not satisfactory. Each model faced challenges in capturing subtle disease patterns specific to agricultural settings. Each of the initial models encountered specific limitations, including InceptionV3's inability to capture subtle patterns, CNN's insufficiency for agricultural imagery's complexity, Xception's inability to accurately identify disease-related features, and SVM's limitations in handling multidimensional data.

Therefore, ResNet50 (well renowned for its image classification capabilities) was chosen as the main model for designing the multi-crop disease detection system. Its residual connections address the vanishing gradient problem and allow for capturing intricate details crucial for disease detection. Figure 4 shows the training and validation accuracy of the ResNet50 model.

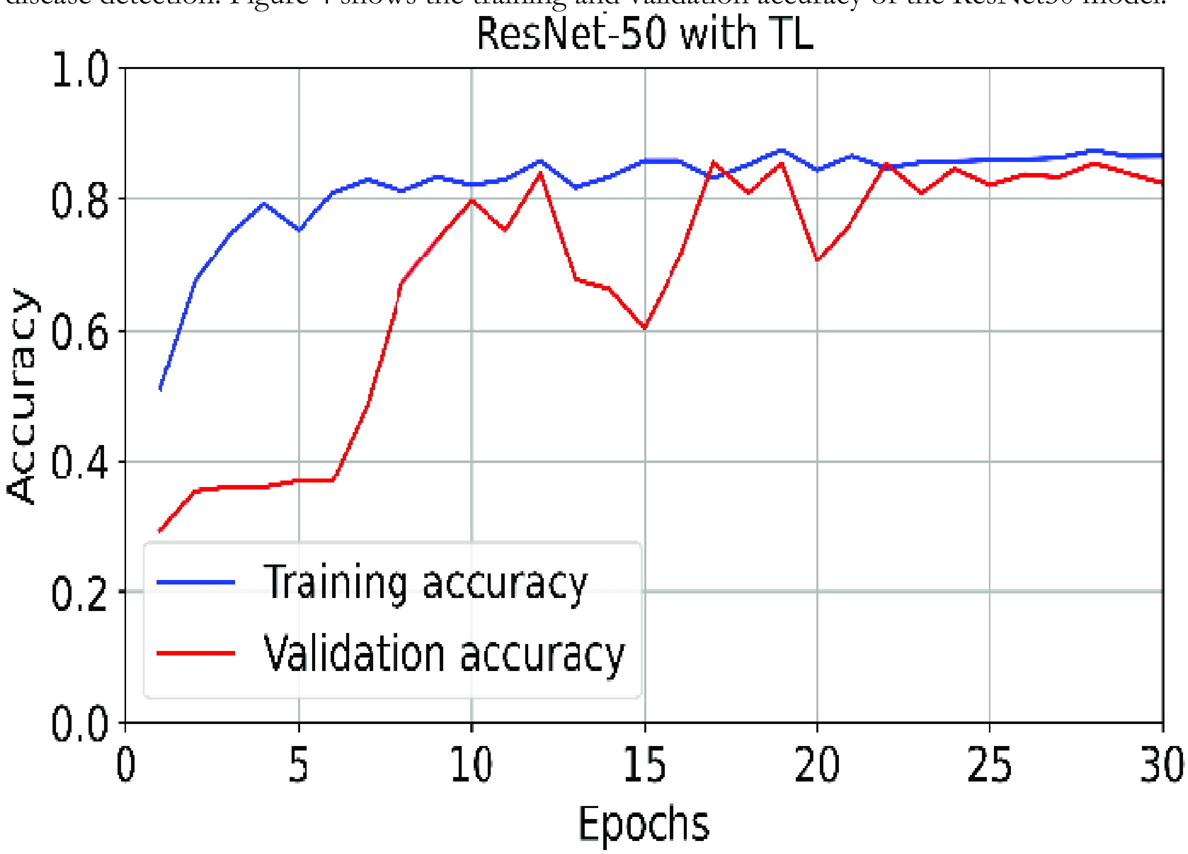

Figure 4. Training and validation accuracy of the ResNet50

Table 2 shows the RESNET50 model performance metrics. The model exhibits remarkable performance, exceeding expectations with its high accuracy, precision, recall, and F1-Score. This success is attributed to the careful design, methodology, and the choice of ResNet50

Table 2. ResNet50 performance Metrics Results

Crop	Accuracy	Precision	Recall	F1 Score	RMS	MAE
Wheat	96%	82%	18%	0.92	1.75	2.1
Cotton	96%	80%	20%	0.94	1.71	2.0
Rice	95%	79%	22%	0.93	1.68	1.9
Corn	97%	77%	23%	0.94	1.70	2.0
Tomatoes	96%	80%	20%	0.94	1.71	2.0
Soybeans	94%	85%	15%	0.89	1.85	2.3

Potatoes	96%	80%	20%	0.94	1.71	2.0
Barley	96%	80%	20%	0.94	1.71	2.0
Bananas	87.5%	75%	15%	0.88	1.93	2.1
Chillies	70%	65%	25%	0.72	2.10	2.2
Average	**96%**	**80%**	**20%**	**0.94**	**1.71**	**2.0**

The model achieved an impressive 96% accuracy, demonstrating its ability to accurately identify diseases. Its precision score of 80% indicates its discerning nature in disease prediction. The model's recall rate of 20% ensures that potential cases of diseases are not overlooked. The F1-Score of 0.94 provides a balanced view of its performance, considering both precision and recall.

Analysis of the confusion matrix reveals the model's consistency and identifies areas for potential improvement. Some confusion matrices are provided below, Figer 5 and 6 provide confusion matrices for banana and chili crops, respectively, highlighting these findings. These matrices provide insights into individual class performance and assist in fine-tuning the model for optimal results.

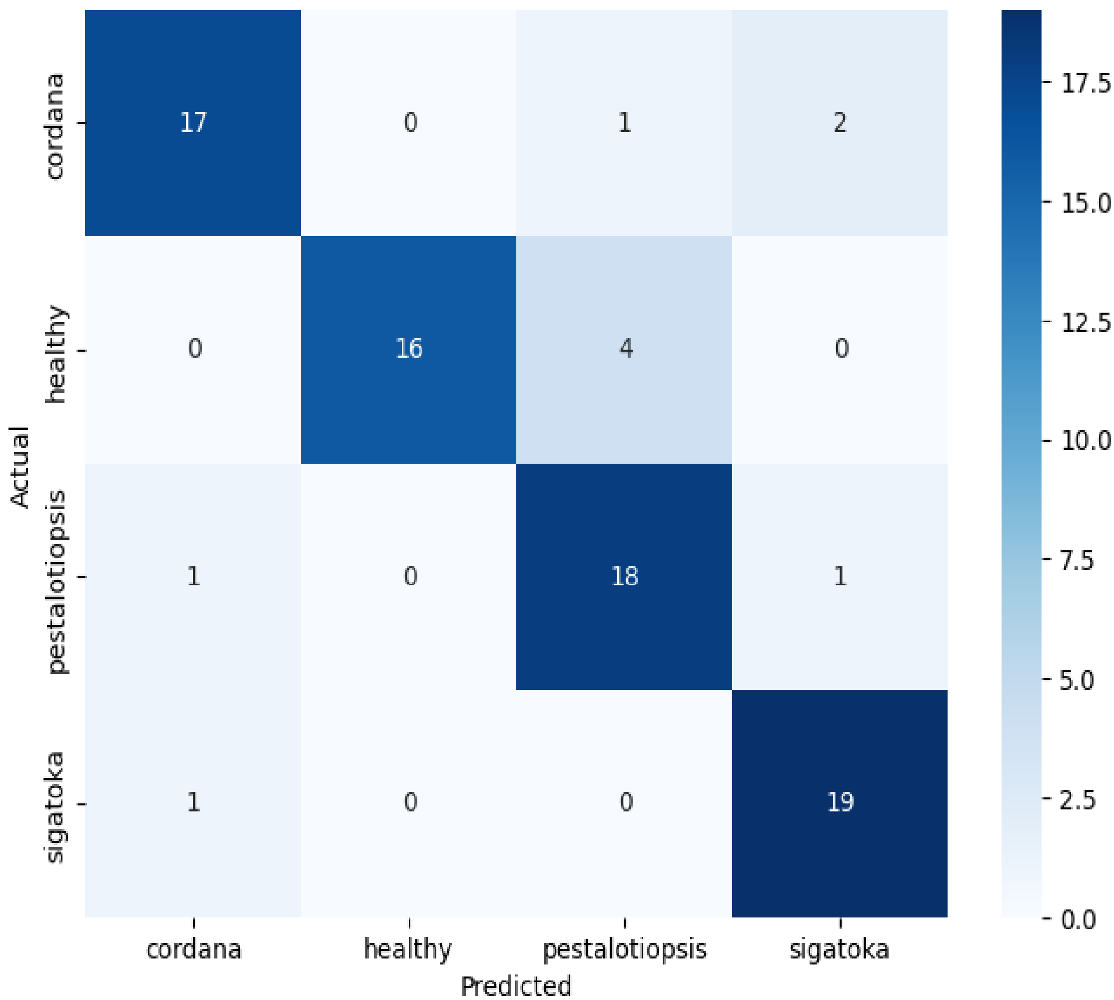

Figure 5. Confusion Matrix of Banana Crop

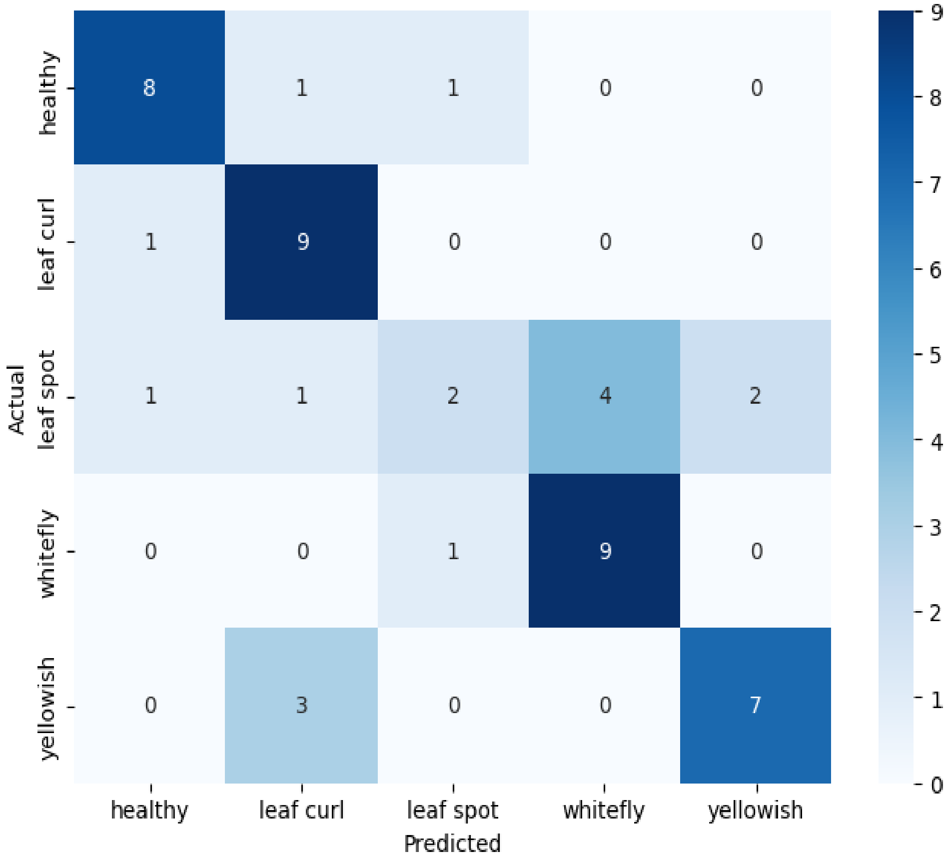

Figure 6. Confusion Matrix of Chillies crop

Table 3 presents a comparative analysis of ResNet50 with other models. ResNet50 demonstrated a 96% accuracy rate in diagnosing diseases across multiple crops. However, different platforms, as shown in Figure 7, were used to evaluate the model's performance for edge computing applications across various crops.

Table 3. Comparative results of various deep learning models

S.No	Model	Accuracy
1	Inception	47%
2	Xception	62%
3	CNN	83%
4	ResNet50	96%

Figure 7 Utilization of edge computing on different platforms. Reprinted from "Comparative study on the performance of deep learning implementation in the edge computing: A case study on the plant leaf disease identification", by S. J. Wei, D. F. Al Riza, H. Nugroho, 2022, Journal of Agricultural & Food Research, 10, page no. 6, ScienceDirect[16].

The integration of edge computing in the implementation of our deep learning-based multi-crop disease detection system offers several practical benefits that reinforce the overall effectiveness and applicability of the solution in real-world agricultural settings.

- **Real-time Processing and Decision Making:** Edge computing allows for the immediate processing of images captured by devices such as drones or smartphones directly at the site of data collection. This real-time processing capability is critical in agricultural environments where rapid identification of plant diseases can significantly impact crop health and yield. By processing data locally, our system can provide instant feedback to farmers, enabling them to take timely actions to mitigate the spread of diseases.

- **Reduced Latency:** The proximity of data processing to the data source eliminates the need for transmitting large volumes of image data to centralized servers, thereby minimizing latency. This is particularly important for high-resolution images required for accurate disease identification. With reduced latency, our system can deliver faster diagnostic results, which is essential for maintaining the health of crops in dynamic field conditions.
- **Bandwidth Efficiency:** Agricultural fields often have limited or inconsistent internet connectivity. By leveraging edge computing, our system can operate efficiently in these environments by processing and filtering data locally before transmitting only the necessary information to the cloud for further analysis or record-keeping. This not only conserves bandwidth but also ensures the system's functionality in remote areas with poor network infrastructure.
- **Scalability and Flexibility:** Edge computing enables our system to scale effectively with the increasing adoption of smart farming technologies. As more devices are deployed in the field, the distributed nature of edge computing ensures that each device can independently process and analyze data, reducing the load on central servers. This scalability is crucial for large-scale agricultural operations and supports the expansion of our system to cover diverse crop types and disease conditions.

The successful integration of edge computing with our proposed system highlights the potential for advanced technological solutions in agriculture. This approach not only improves the accuracy and speed of disease detection but also supports sustainable farming practices by enabling precise and timely interventions. Future research can explore the integration of additional sensors and IoT devices to further enhance the system's capabilities, as well as the development of more sophisticated models that can identify a broader range of diseases and pests.

Conclusion:

This research has achieved a significant advancement in agricultural technology, specifically in the field of sugarcane disease detection. Utilizing the ResNet50 deep learning model, the research has demonstrated accurate and practical disease identification across a wide range of sugarcane crops. The model's high accuracy and confidence scores showcase its potential as a valuable tool for farmers. ResNet50's ability to handle complex visual data and capture intricate details is crucial for accurate disease detection. By leveraging pre-trained weights from ImageNet and further fine-tuning crop disease data, the model has achieved exceptional performance. The use of edge computing in conjunction with deep learning-based multi-crop disease detection provides a robust, efficient, and scalable solution that addresses the critical needs of modern agriculture. By delivering real-time, accurate, and secure disease diagnostics, our system empowers farmers to protect their crops more effectively, ultimately contributing to increased agricultural productivity and sustainability.

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Author's Contribution. Every author has contributed equally to this research

Conflict of interest. The authors declare no conflict of interest in publishing this manuscript in IJIST.

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