Smart Surveillance for Millet Health: An Innovative System for Disease Detection

|  |  |  |
| --- | --- | --- |
|  | Aditya Sharma *School of Computer Science and Engineering* *Lovely Professional University* Phagwara, Punjab, India. adityasharma96458@gmail.com |  |
|  |  |  |

Abstract— The Millet Disease Detection System offers an automated approach to disease diagnosis and management by identifying millet crop illnesses using deep learning models. To categorize photos of millet leaves into healthy and diseased groups, the system uses a number of pre-trained Convolutional Neural Networks (CNNs), such as MobileNetV2, ResNet50, ResNet101, and ResNet152. To improve the resilience of the model, extensive data augmentation approaches were used. While ResNet101 had the best validation accuracy of 90% among the models under study, MobileNetV2 showed exceptional performance in disease identification with high precision, recall, and F1-score. This study shows how well transfer learning works to identify agricultural diseases and how deep learning techniques can help with early diagnosis, which would eventually boost millet farming productivity. Future research will examine how to optimize models for real-time deployment and incorporate more data sources.

Keywords—Millets, deep learning, transfer learning, Convolutional Neural Networks, MobileNetV2, ResNet.

# INTRODUCTION

Agriculture remains one of the most vital sectors for food security and economic growth globally, particularly in developing nations. Millet, a cereal grain known for its resilience to drought and adverse climatic conditions, is a staple crop in many parts of Asia and Africa. Its importance is underscored by the increasing demand for nutritious food in regions prone to food insecurity. Despite their robustness, millet crops are extremely vulnerable to a variety of illnesses, including as bacterial, viral, and fungal infections, which can cause significant production losses if they are not identified and treated promptly. Early and accurate disease detection is crucial to minimizing these losses, ensuring food supply stability, and supporting farmers' livelihoods.

Traditionally, the detection of plant diseases relies heavily on manual inspections by agricultural experts or farmers. These methods, though effective in some contexts, are time-consuming, require specialized knowledge, and are often limited by the subjective nature of visual assessments. Furthermore, delayed response may worsen the disease's spread and further harm crops if early access to disease-related information is not obtained. There is a growing need for automated, scalable solutions that can help with early disease identification and intervention due to the rising worldwide demand for agricultural output and the need to address the problems posed by climate change.

The Latest evolution in AI, mostly DL, have the potential to revolutionize a number of industries, including agriculture. One type of deep learning technique that has shown great promise in picture analysis and classification is Convolutional Neural Networks (CNNs). CNNs are perfect for applications like plant disease detection because they excel at tasks like image recognition, pattern identification, and classification. In recent years, transfer learning—using pre-trained models on large datasets and fine-tuning them for particular tasks—has gained popularity since it significantly reduces the need for massive quantities of labeled data while still improving the model's performance.

This work introduces the Millet Disease Detection System, which uses deep learning-based techniques to overcome the difficulties associated with early disease detection in millet crops. To determine if millet leaf photos are healthy or diseased, the system uses a number of pre-trained models, which are MobileNetV2, ResNet50, ResNet101, and ResNet152. Even with a very small dataset, the models can apply their prior knowledge gained from large-scale picture datasets, like ImageNet, to the millet disease detection problem thanks to the application of transfer learning which is been used.

A scathing aspect of this analysis is the implementation of extensive data augmentation techniques. These techniques, including transformations such as rotation, zooming, and flipping, enhance the diversity of the training data. This reduces the risk of overfitting and improves the model's ability to generalize. Training on augmented data enables models to better manage real-world variability, such as differences in lighting, angles, or backgrounds in leaf images.

The models are assessed using standard metrics such as accuracy, precision, recall, and F1-score, emphasizing their effectiveness in distinguishing between healthy and diseased leaves. Their performance is compared to identify the most effective approach for detecting diseases in millet crops. By incorporating these deep learning models into a practical system, this research seeks to equip farmers with an automated disease detection tool, offering faster and more accurate diagnoses than traditional methods.

The efficacy of disease control in millet farming might be greatly increased by the suggested approach. Automated techniques for early detection can result in speedier treatments, limiting crop losses and the spread of diseases. Furthermore, the system may be used in a variety of agricultural contexts, providing scalability and flexibility to accommodate crop varieties other than millet. The wider ramifications of this study underscore the increasing significance of artificial intelligence (AI) and DL in precision agriculture, where intelligent systems may promote sustainable agricultural methods and improve global food security.

With population increase, resource constraint, and climate change putting further strain on the agriculture sector, creative solutions like the Millet Disease detection with population increase, resource constraint, and climate change putting further strain on the agriculture sector, creative solutions like the Millet Disease Detection System can play a pivotal role in ensuring that crop production remains efficient, sustainable, and resilient. Future work in this domain will focus on enhancing the dataset with more diverse crop images, exploring real-time deployment strategies, and optimizing model performance for faster and more reliable predictions in operational environments.

# LITRATURE REVIEW

[1] In order to monitor millet crops and identify diseases like blast and rust, Mishra et al. suggest a sustainable framework that combines deep learning with the Internet of Things. This framework enables real-time data collection and disease detection through the use of sensors that send data to a Raspberry Pi and cloud server via an automated crop health data-gathering system. Farmers receive notifications when anomalies occur using a hybrid Customized Convolutional Neural Network model that recognizes illness signs. With a high accuracy of 98.8%, this model is a scalable and affordable solution that increases the output and dependability of millet crops.

[2] Kundu et al. created the "Automatic and Intelligent Data Collector and Classifier," an IoT and machine learning-based platform for identifying pearl millet infections. With a high accuracy of 98.78%, the Custom-Net model, which is installed on a Raspberry Pi and cloud server, can classify illnesses like blast and rust. This model integrates transfer learning for improved feature extraction and significantly reduces training time by 86.67%, making it efficient and affordable for farmers. The study shows that such a framework can streamline disease detection, allowing farmers to boost crop quality and yield effectively.

[3] Chaturvedi et al. look at using Convolutional Neural Networks (CNN) to recognize and categorize pearl millet illnesses from photos of the leaves. Using a dataset of 2074 photos, this study categorizes four disease types—ergot, downy mildew, rust, and blast—alongside healthy plants. According to training findings, CNN performs better in terms of accuracy and loss than more conventional models like naïve Bayes, decision trees, support vector machines, and random forests. This study provides a trustworthy tool for precision agriculture in crop disease management and highlights CNN's efficacy in diagnosing plant illnesses.

[4] Pramitha et al. discuss the deployment of mobile technology for smart agriculture, focusing on disease detection in pearl millet. The study highlights how mobile applications linked with sensors, satellites, and drones allow farmers to gather real-life data on soil, water, and disease conditions, enabling better crop management. This chapter emphasizes mobile technology's potential to enhance crop quality by providing crucial data on climate, soil, and pests. Such technology offers timely alerts, aiding farmers, especially in underdeveloped regions, to make informed decisions and prevent crop loss.

[5] Waldamichael et al. review ML approaches for disease detection in cereal plants in crops, which are vital for global food security. In order to reduce production losses, they highlight the need of early disease diagnosis by analyzing 45 research that concentrate on six different varieties of grain. The best techniques for illness detection, according to the scientists, are deep convolutional neural networks trained on hyperspectral data and transfer learning. This review underscores the challenges posed by the lack of public datasets and advocates for the broader application of machine learning in agriculture to enhance food production.

[6] Shahi, Tej Bahadur, et al. (2023). "Recent advances in crop disease detection using UAV and deep learning techniques." Remote Sensing 15.9: 2450. This paper explores the challenges of managing sloping terrains, particularly in regions with mixed fruit tree cultivation, using UAVs imagery and DL techniques. They proposed a method that uses multispectral and optical cameras mounted on UAVs to collect imagery for classifying fruit trees, roads, and buildings. Convolutional Neural Networks (CNN) were employed for image recognition, with VGG-16, VGG-19, and ResNet-50 being compared for accuracy. The study revealed that VGG-16 performed well with multispectral imagery, and the integration of image fusion techniques, such as Principal Components Analysis (PCA), improved prediction accuracy significantly, demonstrating the capability of UAVs-based solutions for precision agriculture in challenging terrains.

[7] Li, Lili, Bin Wang, and Shujuan Zhang (2021). "Plant disease detection and classification by deep learning—a review." An overview of the developments in DL methods for plant disease diagnosis is given in this review study. The authors talk about how deep learning has emerged as a key technology in agricultural plant protection, providing advantages over conventional techniques for identifying plant diseases by facilitating feature extraction and automatic learning. The study examines the advantages and difficulties of using a variety of DL models and imaging methods for plant disease detection. Moreover, the authors discuss how these advancements have led to more accurate and efficient disease detection, thus enhancing research and technology transfer in agricultural systems.

[8] Zanzaney, Archishman Udaysinha, et al. (2023). "Crop Disease Detection Using Deep Neural Networks." In this study, the authors propose the use of DL models, particularly ResNet50, to detect pest attacks and plant diseases using leaf images. The system not only classifies the diseases but also provides countermeasures, including the scientific name of the pest, recommended climatic conditions, and pesticide applications. The approach aims to provide farmers with valuable, actionable information in both English and local languages. The study demonstrated high prediction accuracy, with the model achieving 99.05% accuracy for tomato crops and 99.52% for potato crops, showing its potential for broad agricultural applications.

[9] Kane Amath Sada, Faye Mohameth, and Chen Bingcai. (2020). "Plant disease detection with deep learning and feature extraction using plant village." Computer and Communications Journal 8.6: 10–22. A computer vision-based method for the early identification of leaf illness in agriculture is presented in this work. In order to identify plant leaf diseases, the authors used a multiclass support vector machine classifier using the AlexNet-Honey Badger technique for feature selection and classification. In terms of important performance criteria like F1 score, recall, precision, and accuracy, the hybrid approach—which makes use of the Honey Badger optimization algorithm—performed better than conventional techniques. According to the findings, combining AlexNet with the Honey Badger algorithm boosts feature extraction and convergence rates, making it a significant addition to ML-based plant illness identification.

[10] Li, Zhang, and Wang provide a extensive review of DL applications in plant disease detection. They examine how DL improves objectivity in feature extraction and accelerates research and technological advancements in agricultural plant protection. The paper discusses trends, challenges, and limitations in using deep learning and advanced imaging for crop disease detection, noting its strengths in automated analysis. This paper highlights the increasing influence of artificial intelligence in agricultural technology and is a useful tool for researchers looking to improve plant disease diagnosis and pest management.

[11] Kulkarni discusses a deep learning approach to crop disease detection, addressing challenges posed by climate change and weakened crop immunity. By using computer vision to categorize crop leaf photos as either healthy or unhealthy based on visual patterns, the program helps farmers spot illnesses quickly. The paper emphasizes the use of publicly available datasets to train the model, making it accessible for large-scale agricultural applications and reducing the need for expert intervention in disease management.

[12] Ahmed and Yadav (2023) explore ML approaches for early plant disease detection, utilizing models like RF, KNN, linear regression, and SVC. High-resolution drone imagery is analyzed using grey-level co-occurrence matrices to identify disease signs. According to the study, ensemble models perform better than individual techniques, improving forecast accuracy and allowing for prompt crop damage prevention measures.

[13] A thorough analysis of DL methods for plant disease detection is given by Ahmad, Saraswat, and El Gamal (2023), who also point out prospects and problems in tool development. Key topics such as dataset requirements, imaging sensors, model generalization, illness severity prediction, and human-comparable accuracy are highlighted by their analysis of more than 70 publications. The evaluation provides a road map for filling existing gaps, highlighting the necessity of instruments that help farmers control illnesses and increase agricultural output.  
[14] A crop disease diagnosis system based on the YOLO object identification model—which is renowned for analyzing images in real time at 45 frames per second—is proposed by Morbekar, Parihar, and Jadhav. YOLO divides images into grids, predicting bounding boxes and class probabilities, enabling quick and accurate disease identification. This helps farmers respond promptly, reducing the risk of widespread crop damage.  
 [15] Shahi et al. review the use of UAVs and DL in crop disease detection, emphasizing their role in precision agriculture by delivering vital crop health data. The paper categorizes UAV-based methods, evaluates machine learning techniques, and highlights the benefits of early disease detection. It also addresses challenges and opportunities, suggesting future research directions in agricultural technology.

# PROPOSED METHODOLOGY

The PlantUML graphic that follows gives a visual summary of the complete process and summarizes the general flow of the suggested technique. As illustrated in Figure 1, this study proposes DL-based picture classification method that uses CNNs to automate the classification of crop illnesses. Data preparation, model construction, model training, evaluation, and other crucial phases comprise the methodology's framework, and deployment through a Flask application for real-time inference. The proposed approach leverages pre-trained models, namely MobileNetV2, ResNet50, ResNet101, and ResNet152, to optimize the performance of crop disease classification.

## Data Collection and Preprocessing

The dataset used for training the models consists of images of various crops. As shown in Figure-2. The photos are tagged appropriately, and the dataset is arranged into subdirectories that correspond to various crop classes. To improve the model's resilience and avoid overfitting, data augmentation methods including rotation, zooming, flipping, and shifting are applied to the training dataset. To satisfy the input specifications of the pre-trained models, the photos are scaled to a uniform shape (224x224 pixels). To assess the model's performance, the dataset is divided into subsets for training (80%) and validation (20%).

A diagram of a process

Description automatically generated

Figure Proposed Flow Chart for the model.

## Model Development

To develop the model, we leverage transfer learning by using pre-trained deep learning architectures—MobileNetV2, ResNet50, ResNet101, and ResNet152—as the foundational models. These architectures, originally trained on the large-scale ImageNet dataset for image classification, are fine-tuned to adapt specifically to the crop classification task. The base models are used as feature extractors, with the final layers replaced by custom fully connected layers tailored to the binary or multi-class classification problem.

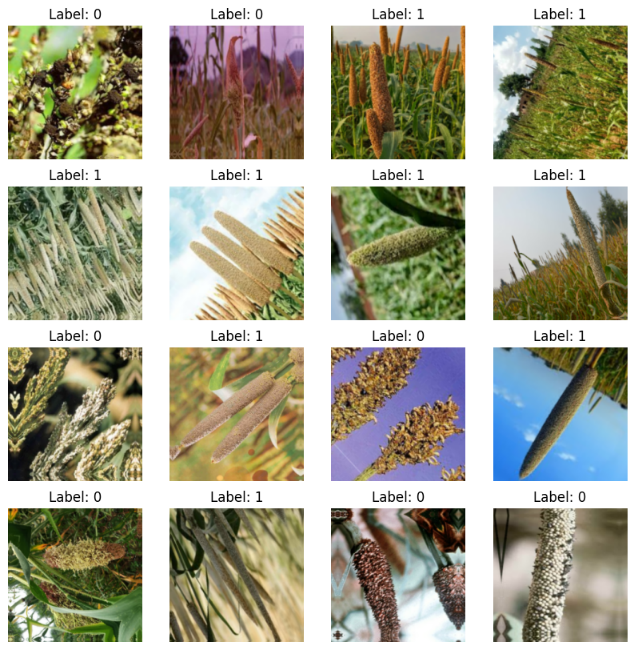


Figure Data collected for sampling

Only the recently added classification layers are trained during the initial training phase, as the basic model layers are frozen to prevent overfitting and lower computational costs. The models are trained using the Adam optimizer with a learning rate of 1e-4 and a sparse categorical cross-entropy loss function.

## Model Training and Evaluation

To make sure the models generalizes effectively to unknown data, the training procedure includes tracking the accuracy of both training and validation as well as the loss. Early stopping is employed to prevent overfitting; if, after a certain number of epochs, the validation loss does not reduce, the training process is terminated. A learning rate scheduler is also used to dynamically modify the learning rate in response to the model's training progress. A distinct validation dataset is used to assess each model, and important performance measures like classification report, confusion matrix, accuracy, and loss are calculated. The top-performing model for the crop classification task is then determined by comparing the models.

The figure is the plot of confusion matrix so that the accuracy of the model can be judged. From the figure the outcome which comes into mind is that the model was trained well because most of the elements are present diagonally.

A diagram of a confusion matrix

Description automatically generated

Figure Confusion Matrix.

## Model Deployment via Flask

The final trained model is integrated into a Flask web application for real-time crop disease classification. The Flask application accepts input images of crops, processes them using the pre-trained model, and returns the predicted disease classification to the user. With the help of the online application's intuitive UI, users may input cropped photos and get real-time forecasts.

# RESULT

Here, four distinct deep learning models—ResNet50, ResNet101, ResNet152, and MobileNetV2—are used to assess the effectiveness of the suggested Millet Disease Detection System. Validation accuracy, validation loss, and classification metrics including precision, recall, and F1-score were used to assess these models for the "With Diseases" and "With No Diseases" classes.

## A. Evaluation Metrics

The training process focuses on tracking both training and validation accuracy, along with loss, to ensure the model effectively generalizes to unseen data. Early stopping is applied to avoid overfitting, halting the training if validation loss does not improve within a set number of epochs. Additionally, a learning rate scheduler is employed to dynamically adjust the learning rate based on the model's progress during training. Each model is tested on a separate validation dataset, with performance metrics such as loss, accuracy, confusion matrix, and classification report being calculated. Finally, the models are compared to determine the most effective one for the crop classification task.

## B. Performance of Individual Models

## 1. ResNet50

The ResNet50 model achieved a validation accuracy of 85.00% with a validation loss of 0.3222. Although the accuracy is respectable, it was lower compared to the other models in this study. The model demonstrated that, while effective, ResNet50 might require further tuning or additional data for improved classification performance.

## 2. ResNet101

The ResNet101 model demonstrated superior performance compared to other models, achieving a validation accuracy of 90.00% and a validation loss of 0.1796. Its deeper architecture allowed it to extract more intricate features from the millet leaf images, enhancing its ability to differentiate between healthy and diseased leaves effectively.

## 3. ResNet152

The ResNet152 model attained a validation accuracy of 85.00% and a validation loss of 0.3305. Despite its increased depth compared to ResNet50, its performance was comparable to that of ResNet50. This suggests that, in this case, the increased depth did not lead to a significant improvement, possibly due to overfitting or the complexity of the dataset.

## 4. MobileNetV2

The MobileNetV2 model achieved a classification accuracy of 89.00%, demonstrating strong performance despite being a lightweight model. The detailed classification metrics for MobileNetV2 are shown in Table-1.

Table CLASSIFICATION REPORT FOR MOBILENETV2

|  |  |  |  |
| --- | --- | --- | --- |
| **Class** | **Precision** | **Recall** | **F1-Score** |
| **With Diseases** | 0.85 | 0.94 | 0.9 |
| **With No Diseases** | 0.93 | 0.84 | 0.88 |
| **Accuracy** | - | - | 0.89 |
| **Macro Average** | 0.89 | 0.89 | 0.89 |
| **Weighted Average** | 0.89 | 0.89 | 0.89 |

A graph of a graph of a graph of a graph of a graph of a graph of a graph of a graph of a graph of a graph of a graph of a graph of a graph of

Description automatically generated

Figure Train and Validation Accuracy graph for model MobileNetV

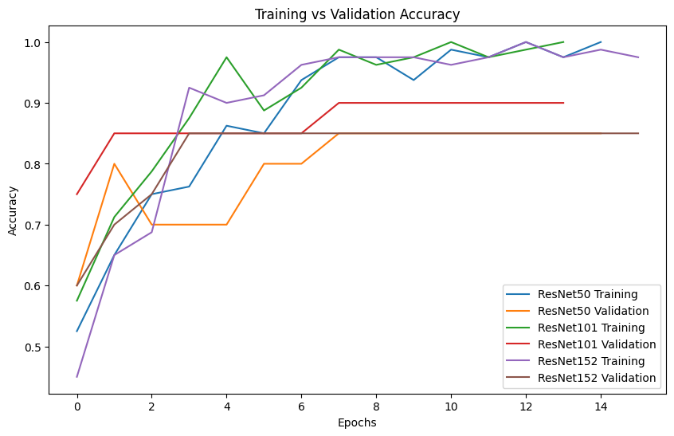
The MobileNetV2 model exhibited strong performance in precision and recall for both healthy and diseased leaves. It achieved a precision of 0.85 and a recall of 0.94 for diseased leaves, highlighting its effectiveness in accurately identifying them. For healthy leaves, the model recorded a precision of 0.93 and a recall of 0.84, maintaining a balanced performance across both categories. The overall F1-scores were 0.90 for diseased leaves and 0.88 for healthy leaves.

## C. Comparative Performance Of All Models

Table II presents a comparative examination of the models. With a validation accuracy of 90.00%, ResNet101 outperformed the other models, followed by MobileNetV2 at 89.00%. The validation accuracy of the ResNet50 and ResNet152 models was 85.00%.

Table Accuracy Table of models.

|  |  |  |
| --- | --- | --- |
| **Model** | **Validation Accuracy (%)** | **Validation Loss** |
| **ResNet50** | 85 | 0.3222 |
| **ResNet101** | 90 | 0.1796 |
| **ResNet152** | 85 | 0.3305 |
| **MobileNetV2** | 89 | 0.47 |

Comparison of ResNet model and it’s variants training is shown by Figure-4b. It is observed that there is similar kind of difference in the Validation and Training graph plotted. All models performed similar, but RestNet101 is at the top as it has the highest accuracy. Figure Accuracy graph for Train and Validation for ResNet50, ResNet101, ResNet152 models

Close-up of a corn plant

Description automatically generated

Figure Predicted Outcome of the MobileNetV2 model

Figure-5 is the Predicted output of the model which we have used. After converting the model in to Pickle the imaged is given as input for the classification task.

## D. Discussion

The results reveal important insights, with ResNet101 achieving the highest validation accuracy among all models. This superior performance can be attributed to its deeper architecture, which effectively captures complex patterns in the data. These findings suggest that deeper models are well-suited for challenging image classification tasks such as agricultural crop disease detection.

MobileNetV2, a lightweight and efficient architecture, performed commendably with an accuracy of 89.00%. Its high recall for diseased leaves (0.94) highlights its effectiveness, particularly in real-time applications within resource-constrained environments. These findings demonstrate that MobileNetV2 strikes a favorable balance between performance and computational efficiency.

# FUTURE PROSPECTIVE

This study highlights the effectiveness of deep learning models in detecting millet diseases, but there are numerous opportunities for further improvement and expansion. Future research could explore the following areas to enhance the performance and broaden the applicability of these models:

1. Expanded and Diverse Datasets: While the current dataset is adequate for training, future work could benefit from incorporating a broader range of millet diseases, capturing different stages of disease development, and including images captured under diverse environmental conditions such as varying lighting and weather. A more diverse dataset would help the models generalize better to real-world scenarios and improve accuracy when deployed in different geographical locations.
2. Advanced Data Augmentation and Synthetic Data Generation: To reduce overfitting and improve model robustness, advanced augmentation methods, such as style transfer or the use of generative adversarial networks (GANs), could be employed to create synthetic images of diseased crops. This approach would enhance the diversity of training samples, particularly for rare diseases, and contribute to developing more resilient models.
3. Model Ensembling and Hybrid Approaches: Combining multiple models through ensemble learning could improve accuracy and robustness. Techniques like bagging, boosting, or stacking could leverage the strengths of different architectures, such as combining ResNet and MobileNetV2 for better generalization across various disease types and conditions. Additionally, exploring hybrid models that combine the power of convolutional neural networks (CNNs) with traditional machine learning techniques could lead to better performance in specific contexts.
4. Integration with Real-Time and Edge Computing: Real-time disease detection is essential for agricultural applications. Future research should focus on optimizing the trained models for deployment on edge devices or mobile platforms with limited computational resources. Methods such as model pruning, quantization, and distillation can be utilized to reduce model size and enhance inference speed while maintaining accuracy.
5. Integration with Other Agricultural Tools: The disease detection system could be enhanced by integrating it with other technologies, such as satellite imagery, drones, or IoT sensors, to monitor crops in real-time. This would allow farmers to identify and address crop diseases early, leading to better crop management and higher yields.
6. Explainable AI (XAI) in Disease Detection: As AI models become more prevalent in critical sectors like agriculture, ensuring their interpretability is vital. Future research should explore the integration of explainable AI (XAI) techniques to offer insights into the decision-making processes of these models. This would help farmers and agricultural experts understand the rationale behind disease detection, fostering greater trust in AI-driven solutions.
7. Collaboration with Agricultural Experts: Close collaboration with agronomists and disease specialists could further refine the model's capabilities. By integrating domain knowledge and expert feedback into the model training process, the system could be fine-tuned to better detect subtle symptoms of diseases, leading to more accurate predictions and more effective preventive measures.

In conclusion, while the current results show promise for deep learning applications in agriculture, there is significant potential to improve and expand these systems. With advancements in dataset quality, model optimization, and integration with other agricultural technologies, AI-driven disease detection systems could play a transformative role in precision farming, enabling more sustainable and efficient agricultural practices.

# Conclusion

Thus the DL models used in this paper for the evaluation of millet disease detection task are ResNet50, ResNet101, ResNet152 and MobileNetV2. The dataset consisted of various images of millet crops infected with different diseases recognizable based on the leaf appearance. Among them, ResNet101 gave the least loss and highest validation accuracy of 90.00%, indicating the capability of the deeper architecture for capturing complicated features.

MobileNetV2, a lightweight model, provided impressive results with a validation accuracy of 89.00%. Because it strikes a good compromise between computing efficiency and performance, this model is especially useful for real-time illness detection applications in mobile or resource-constrained situations. ResNet50 and ResNet152, on the other hand, demonstrated lower validation accuracies (85.00%) in comparison to ResNet101. This could be explained by variables such model complexity and possible overfitting.

Both ResNet101 and MobileNetV2 performed well in recognizing infected and healthy leaves, according to the classification metrics, which included all assessment components. MobileNetV2's remarkable recall for diseased leaves suggested that it may be used practically in agriculture.

Overall, the study demonstrates the effectiveness of using DL models for crop disease detection, with ResNet101 yielding superior results. The results highlight the benefits of deep learning compared to its more classical counterparts, which stem primarily from its high degree of automation and accuracy. Further research may include building on additional datasets and potentially hybrid or transfer learning models to improve performance.

REFERENCE

[1] S. Mishra, et al., "A smart and sustainable framework for millet crop monitoring equipped with disease detection using enhanced predictive intelligence," *Alexandria Engineering Journal*, vol. 83, pp. 298–306, 2023.

[2] N. Kundu, et al., "IoT and interpretable machine learning based framework for disease prediction in pearl millet," *Sensors*, vol. 21, no. 16, p. 5386, 2021.

[3] P. Chaturvedi, et al., "Disease Identification and Classification From Pearl Millet Leaf Images Using Machine Learning Techniques," in *Methodologies, Frameworks, and Applications of Machine Learning*. IGI Global, 2024, pp. 232–243.

[4] J. Pramitha, et al., "Mobile Technology for Smart Agriculture: Deployment Case for Pearl Millet Disease Detection," in *Mobile Application Development: Practice and Experience: 12th Industry Symposium in Conjunction with 18th ICDCIT 2022*. Springer Nature Singapore, 2023.

[5] F. G. Waldamichael, T. G. Debelee, F. Schwenker, Y. M. Ayano, and S. R. Kebede, "Machine learning in cereal crops disease detection: a review," *Algorithms*, vol. 15, no. 3, p. 75, 2022.

[6] T. B. Shahi, et al., "Recent advances in crop disease detection using UAV and deep learning techniques," *Remote Sensing*, vol. 15, no. 9, p. 2450, 2023.

[7] L. Li, S. Zhang, and B. Wang, "Plant disease detection and classification by deep learning—a review," *IEEE Access*, vol. 9, pp. 56683–56698, 2021.

[8] A. U. Zanzaney, R. Hegde, L. Jain, S. S. Choudhuri, and C. K. Sharma, "Crop Disease Detection Using Deep Neural Networks," in *2023 International Conference on Network, Multimedia and Information Technology (NMITCON)*, 2023, pp. 1–5.

[9] F. Mohameth, C. Bingcai, and K. A. Sada, "Plant disease detection with deep learning and feature extraction using plant village," *Journal of Computer and Communications*, vol. 8, no. 6, pp. 10–22, 2020.

[10] L. Li, S. Zhang, and B. Wang, "Plant Disease Detection and Classification by Deep Learning—A Review," *IEEE Access*, vol. 9, pp. 56683–56698, 2021, doi: 10.1109/ACCESS.2021.3069646.

[11] P. Kulkarni, A. Karwande, T. Kolhe, S. Kamble, A. Joshi, and M. Wyawahare, "Plant disease detection using image processing and machine learning," *arXiv preprint*, arXiv:2106.10698, 2021.

[12] I. Ahmed and P. K. Yadav, "Plant disease detection using machine learning approaches," *Expert Systems*, vol. 40, no. 5, p. e13136, 2023.

[13] A. Ahmad, D. Saraswat, and A. El Gamal, "A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools," *Smart Agricultural Technology*, vol. 3, p. 100083, 2023.

[14] A. Morbekar, A. Parihar, and R. Jadhav, "Crop Disease Detection Using YOLO," in *2020 International Conference for Emerging Technology (INCET)*, Belgaum, India, 2020, pp. 1–5, doi: 10.1109/INCET49848.2020.9153986.

[15] T. B. Shahi, et al., "Recent advances in crop disease detection using UAV and deep learning techniques," *Remote Sensing*, vol. 15, no. 9, p. 2450, 2023.