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Research Article

AI-Assisted Classification of Rice Diseases and Insect Pests for Crop Growth Management

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ABSTRACT

Rice is one of the major cultivated crops in India which is affected by various diseases at various stages of its cultivation. Based on their limited expertise, farmers find it incredibly difficult to manually recognize these diseases with high precision. Recent breakthroughs in Deep Learning show that Automatic Image Recognition systems based on Convolutional Neural Network (CNN) and MobileNetV2 models can be quite useful in such situations. The proposed system harnesses the power of machine learning techniques to analyze images of rice plants and identify diseases and pests accurately. A comprehensive dataset of rice plant images, encompassing various disease and pest instances, is collected and used for training a deep learning model. The model leverages convolutional neural networks (CNN) to learn intricate patterns and features representative of different diseases and pests. Through a process of iterative training, the model achieves a high level of accuracy in classifying diseases and pests, enabling real-time detection and intervention. Early diagnosis and effective treatment of rice leaf infections are essential to maintaining the healthy development of rice plants for the attainment of a sufficient food supply that will support the increasing population. Thus, automated disease diagnostic systems can be employed to overcome the shortcomings associated with traditional leaf disease diagnosis methods, which are usually time-consuming, less accurate, and costly. Computer-aided rice leaf disease diagnosis systems are becoming more common in recent times. This paper presents various solutions based on various deep learning approaches. Based on the crop's image data and moreover it presents DL models like CNN and MOBILENET techniques with their performance measure.

Keywords: Rice crop, Plant diseases, Pest detection, Leaf infection, Deep learning, Convolutional Neural Network (CNN), MobileNet, Automatic image recognition, Machine learning. Image classification, Disease diagnosis, Real-time detection, Agriculture technology, Early diagnosis, Food security, Computer-assisted diagnosis, Dataset collection, Pattern recognition, Rice disease detection system, Performance analysis.

INTRODUCTION

I

Agriculture remains the backbone of India's economy, with a large section of the population relying on it for their livelihood. The country's agricultural output has a significant influence on domestic markets and food security. However, challenges such as population growth, unpredictable weather patterns, and changing environmental conditions have compelled the agricultural sector to seek innovative and cost-effective solutions. Plant health plays a crucial role in sustaining agricultural productivity, but crops are increasingly vulnerable to various diseases that can severely impact both yield and quality. Early identification and timely treatment of these diseases are essential to prevent widespread crop loss and minimize the excessive use of pesticides, thereby reducing environmental harm.

Manual detection of plant diseases is only labor intensive, but it also demands considerable expertise and time,

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making it impractical to a large extent. This restriction has led to the adoption of high-tech technological solutions, especially image processing and machine learning, for automated disease detection. The procedure usually involves obtaining images of the plant concerned, preprocessing these images to enhance their quality, segmenting the areas of interest, extracting characteristics, and classifying the illness.

In recent years, deep learning has emerged as a transformative approach in the field of machine learning, providing exceptional capabilities in recognizing complex patterns and features. Its use in detecting plant diseases has remarkably enhanced the accuracy of diagnosing them, which in turn assists in supporting agricultural activities that care for the environment. The most recent deep learning models, alongside data augmentation, feature extraction, and even data visualization techniques, are providing the ability to identify and categorize plant diseases with precision. This development greatly aids in early diagnosis of diseases and effective management of crops, thus supporting Increased productivity as well as food security.

OBJECTIVES

- To create a comprehensive dataset for rice pest images using advanced data augmentation techniques.
- To enhance the accuracy of rice pest image classification through the use of efficient AI algorithms.
- To detect and identify rice diseases effectively and generate timely alerts for farmers.
- To serve as a decision support tool, providing essential data and technical guidance for pest management in rice cultivation.
- To assist stakeholders, including farmers, agricultural inspectors, and experts, in the identification and management of rice pests.

METHODS

- **Dataset creation**:

The foundation of the rice leaf disease detection system lies in the creation of a diverse and comprehensive dataset. Initially, a synthetic dataset was generated using image augmentation techniques such as rotation, scaling, translation, brightness adjustment, and flipping. This was done to simulate various environmental conditions, leaf orientations, and defect types that might be encountered in real-world scenarios. The synthetic images were labeled using expert input and domain knowledge to ensure accuracy in the annotations. Along with this, a real-world dataset was created by capturing images from rice fields across multiple regions using high-resolution cameras under varying weather and lighting conditions. The collected data covered a wide spectrum of disease stages and leaf types, making it suitable for training a highly generalized model.

- **Pre-processing**:

To maintain consistency and improve model efficiency, all images in both datasets underwent an extensive pre-processing pipeline. Noise filtering techniques, such as Gaussian blur and median filtering, were used to eliminate background clutter and artifacts. Image normalization ensured the pixel values were scaled appropriately, while resizing to a uniform input dimension (224x224) facilitated smoother model training. Additional enhancements included histogram equalization for contrast improvement and image sharpening to highlight disease-specific patterns. The pre-processing pipeline was automated to handle both synthetic and field images, ensuring the model received high-quality inputs regardless of data origin.

- **Ensemble model selection**:

For this project, we chose two deep learning models: Convolutional Neural Network (CNN) and MobileNetV2. The CNN was built to extract subtle fine-grained features from images of rice leaves so that it could identify tiny disease symptoms that might not be noticeable to the human eye. Though it had a comparatively greater computational burden, the CNN provided consistent classification outcomes in various classes of diseases. Conversely, MobileNetV2 was selected due to its speed and efficiency. As a light-weight model that has been optimized for mobile and edge devices, it offered quicker inference times while sustaining robust classification performance. This rendered it particularly apt for deployment within real-time resource-limited agricultural environments. The combination of these models provided an equilibrium strategy—focusing both on accuracy as well as usability—which suited our objective of building a pragmatic and accessible disease detection system for deployment in the fields.

- Model training:

Each model was trained using both synthetic and real-world datasets to ensure it could adapt to diverse conditions. Transfer learning was used by leveraging pretrained weights to speed up convergence and enhance overall performance. The training workflow included fine-tuning important hyperparameters like learning rate, batch size, and weight decay, together with choosing an appropriate loss function such as cross-entropy for classification and IoU-based loss for bounding box regression. The training process was conducted in several stages in order to enable incremental improvement. To avoid overfitting and promote model generalization, data augmentation procedures were integrated. Moreover, the training scripts were modularly developed in order to optimize flexibility for deployment in both GPU and CPU settings, thereby ensuring efficiency and flexibility in different hardware configurations.

- Evaluation metrics:

The trained models were evaluated using a robust set of metrics to ensure comprehensive performance analysis. Key metrics included accuracy, precision, recall, F1-score, and mean Average Precision. Confusion matrices were plotted for each disease class to assess misclassification trends. To test generalization, the models were evaluated not only on the validation dataset but also on unseen real-world images taken from different farms. Special focus was placed on the detection of critical diseases such as Leaf Blast, Brown Spot, and Hispa, given their significant impact on rice crop yields. The system's ability to detect early-stage symptoms was also tested.

- Results and analysis:

After training, our models demonstrated reliable performance. The Convolutional Neural Network (CNN) achieved an accuracy of 74.50%, effectively identifying key disease patterns in most cases. MobileNetV2 performed better, reaching an accuracy of 80.50%, and also offered faster inference times, making it well-suited for real-time field applications. Both models handled a variety of image conditions effectively, thanks to the diverse dataset used during training. Confusion matrix analysis showed that major diseases such as Leaf Blast were rarely misclassified. Overall, the system shows strong potential to assist farmers with timely and accurate disease diagnosis, contributing to improved crop management.

In addition to generating synthetic images, the system was trained and validated using a diverse set of real life photographs captured directly from rice fields. These images, collected under various lighting conditions—such as direct sunlight, shadow, and different viewing angles contributed significantly to improving the model’s generalization ability. The combination of synthetic and authentic data enabled the models to effectively recognize diseases even in the presence of noise, inconsistent illumination, and other environmental variables. For this study, we implemented and evaluated two deep learning architectures: a standard Convolutional Neural Network (CNN) and MobileNetV2. These models where chosen for their balance of accuracy and computational efficiency, particularly for deployment on resource-constrained devices. Both models were fine-tuned and assessed using standard classification metrics, demonstrating strong performance in detecting diseases like Leaf Blast, Brown Spot, and Hispa. A consistent pre-processing pipeline was applied to all images, ensuring uniformity across inputs. The final model is embedded within a user-friendly interface designed to deliver quick and reliable diagnostic feedback to farmers, supporting timely interventions and promoting sustainable agricultural practices.

RESULTS

The rice leaf disease and pest classification system were thoroughly evaluated using a mix of synthetic datasets and real images collected from farm environments. Performance was measured using key metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of the models implemented. Among the models tested, the Convolutional Neural Network (CNN) and MobileNetV2 showed the most promising results. CNN achieved an overall result accuracy of 74.50%, demonstrating its capability to distinguish between multiple disease types. MobileNetV2 performed better with a result of 80.50% and also offered faster inference times, making it a suitable option for real- time applications, especially in low-resource settings.

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Confusion matrix analysis indicated that both models achieved high true positive rates for major diseases like Leaf Blast, Brown Spot, and Hispa, with minimal false positives. The use of both synthetic and real-world data played a vital role in improving model generalization across different environmental conditions and image qualities.

These outcomes support the system's potential to assist in early disease detection in agricultural settings. Its lightweight architecture and accessible, web-based interface make it practical for farmers and agricultural experts to diagnose issues promptly and apply appropriate measures to protect crop health and ensure food security.

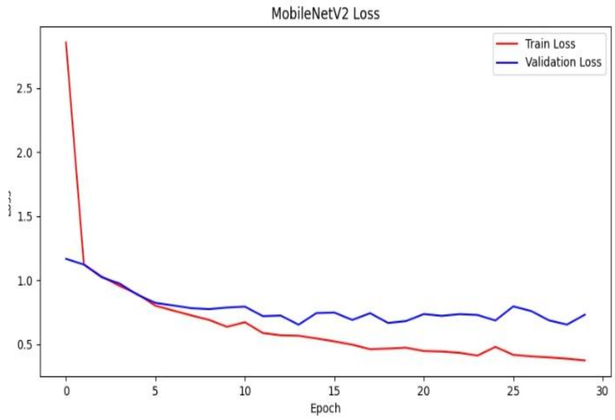

Figure 1: MobileNetV2 Loss

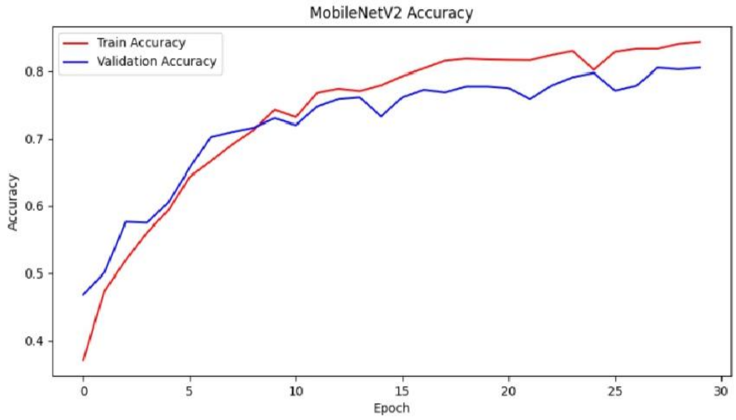

Figure 2: MobileNetV2 Accuracy

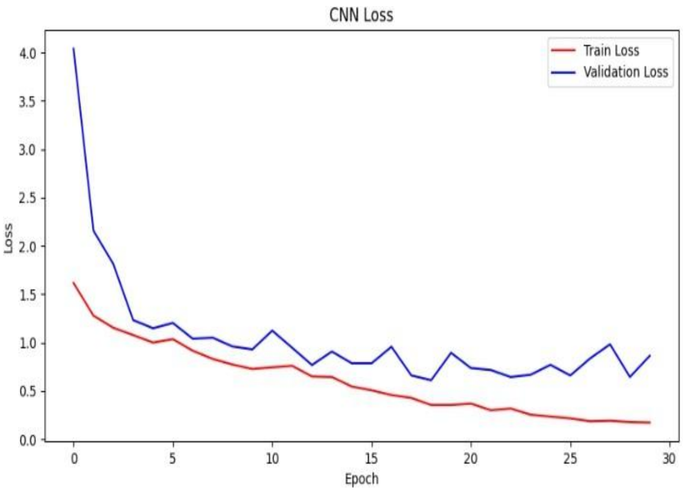

Figure 3: CNN Loss

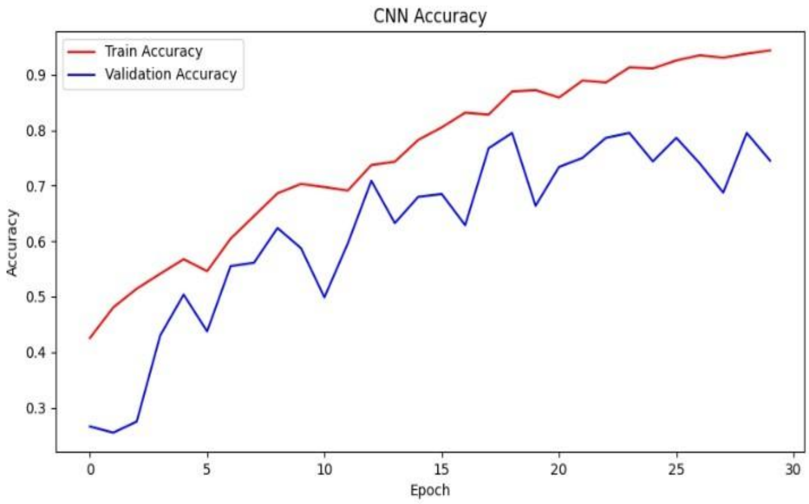

Figure 4: CNN Accuracy

DISCUSSION

The results of this research categorically demonstrate the effectiveness of deep learning models in the accurate detection and diagnosis of rice leaf diseases and pest infestations. Successful implementation of ensemble approaches, which combined models such as CNN, and MobileNet V2, resulted in an optimal approach that leveraged the strengths of each model. The high accuracy provided by CNN and MobileNet V2, among others, validates the potential of convolutional neural networks in agricultural diagnosis, particularly in large-scale applications where timely interventions are paramount.

The ability of the system to process synthetic images as well as field images of real-world environments adds vigor and adaptability to various environmental situations. Use of real-world images, taken under various light intensities, backgrounds, and levels of disease, greatly added value to the training process and the generalization ability of the models. Blending controlled synthetic data with real-world dynamic input reduced the likelihood of model overfitting and enhanced detection performance in real environments.

In addition, the results show that computational efficiency is just as important as accuracy in the context of real-time systems for farmers. The compromise between speed and accuracy of MobileNet V2 makes it highly appropriate for web and mobile use, thus making disease detection devices accessible even in resource-constrained rural areas. The development of a user-friendly, web-based interface further bridges the gap between state-of-the-art AI techniques and end-user usability, making even non-experts benefit from timely and accurate disease identification. Nonetheless, while the models exhibited robust performance in the detection of common diseases, future system development can entail the extension of the dataset to include new diseases and pest varieties to refresh the model in evolving agricultural environments. Furthermore, incorporating geolocation-based disease monitoring and early warning notification can increase the system's applicability in the real world. In general, this study emphasizes the revolutionary potential of artificial intelligence in precision agriculture, enabling farmers to make smart decisions and alleviating global food security issues.

REFERENCES

[1] Pallapothala Tejaswini, "Rice Leaf Disease Classification Using CNN," *IOP Conference Series: Earth and Environmental Science*, 2022.

[2] Shruti Aggarwal, M. Suchithra, N. Chandramouli, Macha Sarada, Amit Verma, D. Vetri Thangam, Bhaskar Pant, and Biruk Ambachew Adugna, "Rice Disease Detection Using Artificial Intelligence and Machine Learning Techniques to Improvise Agro-Business," 2022.

[3] Vimal K. Shrivastava, Monoj K. Pradhan, Sonajharia Minz, and Mahesh P. Thakur, "Rice Plant Disease Classification Using Transfer Learning of Deep Convolution Neural Network," 2022.

[4] G.K.V.L. Udayananda, Chathurangi Shyalika, and P. P. N. V. Kumara, "Rice Plant Disease Diagnosing Using Machine Learning Techniques: A Comprehensive Review," 2022.

[5] Ruoling Deng, Ming Tao, Hang Xing, Xiuli Yang, Chuang Liu, Kaifeng Liao, and Long Qi, "Automatic Diagnosis of Rice Diseases Using Deep Learning," 2021.

[6] Qi, H., Liang, Y., Ding, Q., and Zou, J., "Automatic Identification of Peanut-Leaf Diseases Based on Stack Ensemble," *Applied Sciences*, vol. 11(4), p. 1950, 2021.

[7] R. Salini, A.J. Farzana, and B. Yamini, "Pesticide Suggestion and Crop Disease Classification Using Machine Learning," vol. 63(5), pp. 9015–9023, 2021.

[8] Mahalakshmi, S. D., and Vijayalakshmi, K., "Agro Suraksha: Pest and Disease Detection for Corn Fields Using Image Analysis," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12(7), pp. 7375–7389, 2021.

[9] Ramakrishnan, M., "Groundnut Leaf Disease Detection and Classification by Using Back Propagation Algorithms," in *2015 International Conference on Communications and Signal Processing (ICCSP)*, pp. 0964–0968, IEEE, April 2015.

[10] Ramesh S., Hebbar R., Niveditha M., Pooja R., Shashank N., and Vinod P.V., "Plant Disease Detection Using Machine Learning," in *2018 International Conference on Design Innovations for 3Cs: Compute,*

Communicate, Control (ICDI3C), pp. 41–45, IEEE, April 2018.

[11] Zekiwos, M., & Bruck, A. (2021). *Deep Learning-Based Image Processing for Cotton Leaf Disease and Pest Diagnosis*. Journal of Electrical and Computer Engineering.

[12] Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). *Identification of rice diseases using deep convolutional neural networks*. Neurocomputing, 267, 378–384.

[13] Jayakumar, A. (2020). *Detection and Classification of Leaf Diseases in Maize Plants using Machine Learning*.

[14] Kulkarni, K. C., & Selvanayaki, M. P. (2021). *A Deep Learning-Based System for Automatic Identification of Diseases in Rice Plants*.

[15] Pothen, M. E., & Pai, M. L. (2020, March). *Detection of Rice Leaf Diseases Using Image Processing*. In 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC). IEEE.

[16] Rani, B., Ojha, S., Kaushal, H., Kumar, S., Chowdhury, T. R., Karmakar, S., & Jana, B. (2020). *A Study on Detection of Brown Spot Disease in Rice Plant Using Machine Learning Technique*. International Conference on Recent Trends in Artificial Intelligence, IoT, Smart Cities & Application (ICAISC 2020).

[17] Sethy, P. K., Barpanda, N. K., Rath, A. K., & Behera, S. K. (2020). *Deep feature based rice leaf disease identification using a support vector machine*. Computers and Electronics in Agriculture, 175, 105527.

[18] Kim, E., Deng, R., et al. (2022). *Deep Learning-Based Rice Disease Detection and Classification Using Image Segmentation*. Frontiers in Plant Science, 12.

[19] Wang, Y., Wang, H., & Peng, Z. (2021). *Rice diseases detection and classification using attention-based neural network and Bayesian optimization*. Expert Systems with Applications, 178, 114770.

[20] Krishnamoorthy, N., Narasimha, P. L. V., Pavan, K. C. S., Subedi, B., & Abraha, H. B. (2021). *Rice leaf diseases prediction using deep neural networks with transfer learning*. Environmental Research, 198, 111275.

[21] Singh, S., & Kumar, I. (2021). *Rice plant infection recognition using deep neural network systems*.

[22] Elmitwally, N. S., Tariq, M., Khan, M. A., Ahmad, M., Abbas, S., & Alotaibi, F. M. (2022). *Rice Leaves Disease Diagnosis Empowered with Transfer Learning*.

[23] Pothen, M. E., & Pai, M. L. (2020). *Detection of Rice Leaf Diseases Using Image Processing*. IEEE International Conference on Computing Methodologies and Communication (ICCMC 2020), 978-1-7281-4889-2/20.

[24] Kumar, S., & Kumar, A. (2022). *Automated Detection and Classification of Rice Plant Diseases and Insect Pests using Machine Learning*. International Conference on Soft Computing and Signal Processing.

[25] Nayak, S. S., & Sahu, S. S. (2022). *Machine Learning-based System for Rice Plant Diseases and Insect Pests Detection and Classification*. International Conference on Computer, Communication and Computational Sciences.

[26] Islam, M. R., Hossain, M. N., & Kabir, M. H. (2021). *An Integrated System for Early Detection of Rice Plant Diseases Using Deep Learning and IoT*. IEEE International Conference on Systems, Man, and Cybernetics.

[27] Andrianto, H., Suhardi, Faizal, A., & Armandika, F. (2020). *Smartphone Application for Deep Learning-Based Rice Plant Disease Detection*. 2020 International Conference on Information Technology Systems and Innovation (ICITSI), 387–392.

[28] Qi, H., Liang, Y., Ding, Q., & Zou, J. (2021). *Automatic Identification of Peanut-Leaf Diseases Based on Stack Ensemble*. Applied Sciences, 11(4), 1950.

[29] Salini, R., Farzana, A. J., & Yamini, B. (2021). *Pesticide Suggestion and Crop Disease Classification using Machine Learning*, 63(5), 9015–9023.

[30] Sethy, P. K., Barpanda, N. K., Rath, A. K., & Behera, S. K. (2020). *Deep Feature Based Rice Leaf Disease Identification Using Support Vector Machine*.