



Original Research Paper

A Deep Learning Based Approach for Automated Detection of Seed Health Conditions

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Abstract

Seed health plays a critical role in agricultural productivity, as diseased seeds negatively affect germination and yield. Manual inspection is time-consuming and unsuitable for large-scale evaluation. This study proposes a deep learning framework for automated classification of seed images into healthy and unhealthy categories using transfer learning with pre-trained convolutional neural networks. Data preprocessing and augmentation improve robustness against variations in lighting, rotation, and background. A structured training-testing pipeline prevents data leakage and ensures unbiased evaluation. Performance is assessed using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices. Experimental results demonstrate reliable classification performance, highlighting the effectiveness of transfer learning for scalable seed quality assessment in precision agriculture.

Keywords: Seed health classification, Deep learning, Transfer learning, CNN, Image classification, Precision agriculture.

1. Introduction

Seed quality significantly influences crop yield, economic return, and food security. Early detection of unhealthy seeds is essential to prevent reduced germination and financial loss. Traditional manual inspection methods are labor-intensive, subjective, and impractical for large-scale operations.

Recent advancements in computer vision and deep learning enable automated agricultural image analysis. However, limited labeled data and variations in imaging conditions remain major challenges. Transfer learning addresses these issues by leveraging knowledge from large pre-trained models, improving accuracy and reducing training time.

This study proposes a transfer learning-based deep CNN framework for binary seed health classification with structured evaluation using multiple performance metrics to ensure objective assessment.

2. Literature Survey

Deep learning has emerged as a powerful approach for **automated plant disease detection and agricultural image analysis**, offering significant improvements over traditional image-processing and feature-engineering techniques. Conventional approaches generally depend on manually designed features such as color, texture, shape, and morphological characteristics. The performance of such methods can be affected by variations in illumination, background, image quality, and disease appearance. In contrast, deep learning models, particularly **Convolutional Neural Networks (CNNs)**, can automatically learn hierarchical and discriminative features directly from images, reducing the need for manual feature extraction.

Sladojevic et al. [1] demonstrated the effectiveness of deep neural networks for plant disease recognition using leaf images. Their work showed that CNN-based approaches could automatically learn relevant visual patterns associated with different disease conditions and achieve reliable classification performance. Similarly, Ferentinos [2] investigated deep learning models for plant disease detection and diagnosis and reported high classification performance across multiple plant disease categories. These studies established the potential of CNNs as effective tools for automated agricultural image classification.

Kamilaris and Prenafeta-Boldú [3] provided a comprehensive survey of deep learning applications in agriculture and highlighted the growing importance of CNN-based techniques for tasks such as **crop monitoring, disease identification, plant recognition, and agricultural image analysis**. Their findings demonstrated that deep learning can outperform many conventional machine-learning approaches when sufficient training data and appropriate computational resources are available.

Saleem et al. [4] further reviewed deep learning approaches for plant disease detection and classification, emphasizing the ability of CNN models to automatically extract meaningful visual characteristics from plant images and support automated disease diagnosis.

Although deep learning provides strong performance, training a CNN model from scratch generally requires a **large amount of labeled training data and significant computational resources**. This limitation is particularly important in agricultural applications because collecting and accurately labeling large datasets of diseased and healthy samples can be expensive and time-consuming. **Transfer learning** provides an effective solution to this problem by utilizing knowledge learned from large-scale datasets such as ImageNet and adapting pre-trained models to specific agricultural classification tasks.

Radočaj et al. [5] investigated transfer learning approaches in agriculture and reported that pre-trained deep learning models can provide improved classification performance while reducing training time and computational requirements. In transfer learning, the initial layers of a pre-trained CNN retain their learned feature representations, while the later layers are adapted or fine-tuned for the target classification problem. This approach is particularly useful when the available agricultural dataset is relatively small.

Khandagale et al. [6] proposed a CNN-based approach for multi-crop disease detection and demonstrated the effectiveness of deep feature extraction for agricultural image classification. Their findings indicate that deep CNN architectures can identify complex visual patterns associated with crop diseases and improve classification performance compared with conventional baseline approaches. Additional studies [7]–[10] have also demonstrated the effectiveness of CNN-based deep learning techniques for plant and crop disease identification, further establishing deep learning as an important technology for automated agricultural image analysis.

Despite these significant developments, several **research challenges and limitations** remain. Agricultural image datasets are often limited in size and may contain class imbalance, where one category has substantially more samples than another. Furthermore, variations in **lighting conditions, image background, seed or leaf orientation, camera characteristics, image resolution, disease severity, and environmental conditions** can significantly influence model performance. A model trained using images collected under controlled conditions may therefore produce lower accuracy when applied to images captured in real-world agricultural environments.

Another important observation from the existing literature is that **most research has concentrated on**

plant leaf disease detection, while comparatively fewer studies have focused specifically on **seed health assessment**. Seed quality plays an important role in germination, crop establishment, productivity, and overall agricultural yield. Early identification of unhealthy or defective seeds can therefore support better seed selection and reduce potential crop losses. However, automated binary classification of seeds into **healthy and unhealthy categories** presents different visual challenges compared with leaf disease classification.

Therefore, there is a clear research opportunity to investigate **transfer learning-based deep CNN models for automated seed health classification**. In this study, pre-trained architectures such as **MobileNet, InceptionV3, and DenseNet201** are explored for distinguishing healthy and unhealthy rice seeds. The models are evaluated using multiple performance measures, including **accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analysis**. This systematic evaluation aims to determine the suitability of transfer learning for reliable and scalable seed health assessment and to address the research gap identified in existing agricultural deep learning studies.

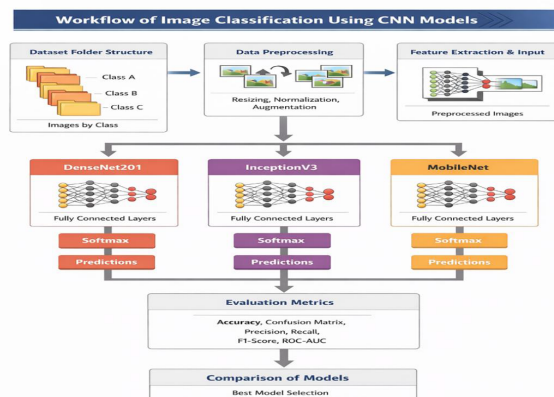


Fig 1: Proposed Model for Checking Healthy and Unhealthy Rice Seeds

3. Models and Materials

3.1 Proposed Model

The proposed system employs transfer learning with **DenseNet201, InceptionV3, and MobileNet architectures**. Preprocessed images pass through convolutional layers for feature extraction, followed by fully connected layers and a softmax classifier for binary prediction. Data augmentation enhances model generalization.

3.2 Dataset Description

The dataset consists of seed images categorized into healthy and unhealthy classes. Images are resized, normalized, and augmented using rotation, flipping, and 3.2 Dataset Description — Continued

zooming techniques. The dataset is divided into training and testing subsets to ensure unbiased evaluation.



Fig 2: Healthy and Unhealthy Rice Seeds

3.3 Transfer Learning

Transfer learning utilizes pre-trained CNN models trained on large datasets such as ImageNet. Convolutional layers are initialized with pre-trained weights, while final layers are retrained for binary classification. This approach reduces training time, improves accuracy, and enhances generalization.

4. Result Analysis

Model performance is evaluated using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC. Training and validation curves are analyzed to detect overfitting or underfitting. Results indicate strong discriminative capability and effective separation between healthy and unhealthy seed classes.

Confusion Matrix: Highlights the number of true positives, false positives, true negatives, and false negatives.

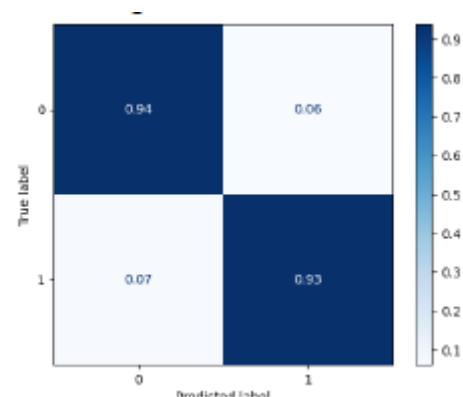


Fig 3: MobileNet Confusion Matrix

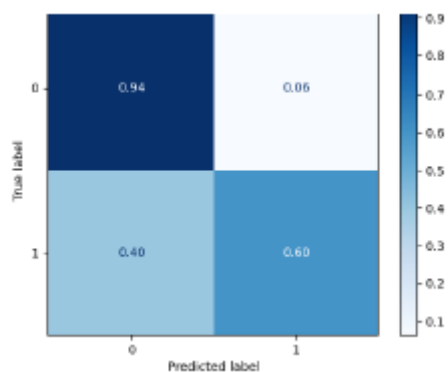


Fig 4: InceptionV3 Confusion Matrix

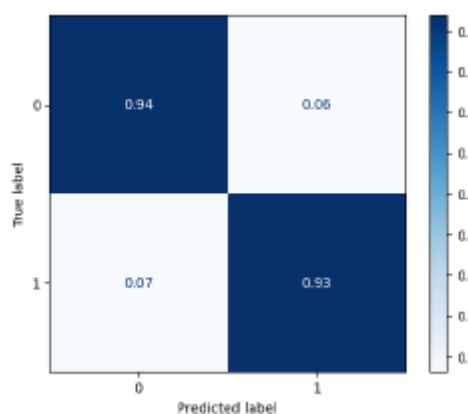


Fig 5: Densenet201 Confusion matrix

Training Curves: Graphs of **training and validation accuracy and loss over epochs** are used to monitor model learning and identify potential **overfitting or underfitting**. Close alignment between training and validation performance indicates good generalization, while a widening gap may suggest overfitting.

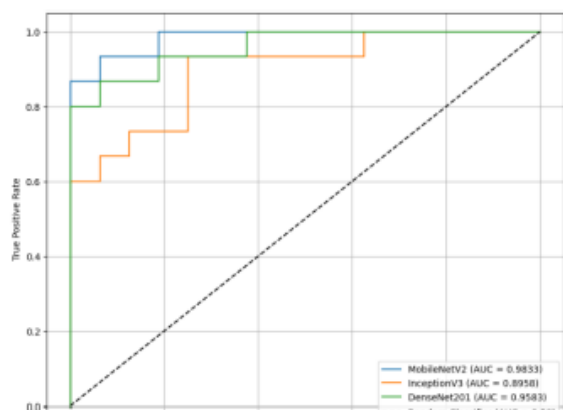


Fig 6: Receiver Operating Characteristic (ROC) Curve

Classification Report: The classification report summarizes model performance using precision, recall, F1-score, and support for each class, providing a detailed class-wise evaluation beyond overall accuracy. These metrics highlight the model's ability to correctly identify healthy and unhealthy crop images while balancing false positives and false negatives.

	precision	recall	f1-score	support
0	0.94	0.94	0.94	16
1	0.93	0.93	0.93	15
accuracy			0.94	31

Fig 7: Classification Report for MobileNet

	precision	recall	f1-score	support
0	0.84	1.00	0.91	16
1	1.00	0.80	0.89	15
accuracy			0.90	31
macro avg	0.92	0.90	0.90	31

Fig 8: Classification Report for InceptionV3

	precision	recall	f1-score	support
0	0.71	0.94	0.81	16
1	0.90	0.60	0.72	15
accuracy			0.77	31
macro avg	0.81	0.77	0.77	31
weighted avg	0.80	0.77	0.77	31

Fig 9: Classification Report for DenseNet201

Author	Description	Dataset Used	Results
Wang et al. (2022) [11]	Applied attention mechanisms and depthwise separable convolution networks for crop leaf disease classification.	Public crop leaf disease image dataset with multiple classes	Accuracy – 94.65%
Radočaj et al. (2024) [5]	Investigated transfer learning-based deep learning models for agricultural image classification and plant disease detection.	Multiple public agricultural image datasets	High classification performance reported
Khandagale et al. (2025) [6]	Proposed a CNN-based framework for efficient multi-crop disease detection using deep feature extraction.	Multi-crop disease image dataset	Improved accuracy compared to baseline CNNs
Current Study	Intelligent deep learning framework for binary crop health	Public crop image dataset categorized into	Consistent and robust classification performance with high

assessment using transfer learning. Evaluation is performed using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analysis.	healthy and unhealthy images	accuracy and strong ROC-AUC values
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5. Discussion

The models demonstrate consistent performance across various evaluation metrics, confirming the effectiveness of transfer learning. However, controlled imaging conditions and limited variability may overestimate real-world performance. Further validation using diverse datasets is recommended.

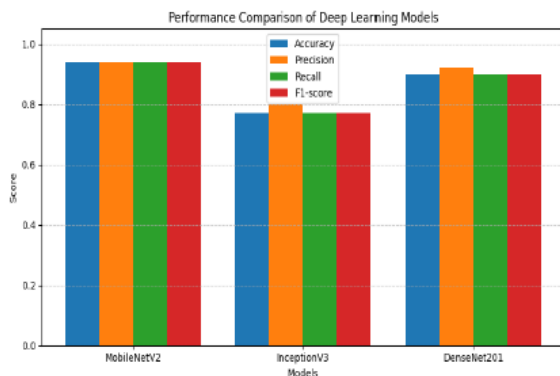


Fig 10: Performance Comparison Between the Trained Models

6. Conclusion and Future Work

This study presented a **transfer learning-based deep Convolutional Neural Network (CNN) framework for automated binary seed health classification**, with the objective of distinguishing between healthy and unhealthy rice seeds. The proposed approach utilizes pre-trained deep learning architectures, including **MobileNet, InceptionV3, and DenseNet201**, to extract meaningful visual features from seed images and perform automated classification. The use of transfer learning reduces the dependence on large-scale labeled datasets and significantly reduces the computational requirements and training time compared with developing a CNN model entirely from scratch.

The experimental results demonstrate that the proposed models are capable of effectively

distinguishing healthy and unhealthy seed samples. The evaluation using **accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices** indicates consistent classification performance across the trained models. The confusion matrices further demonstrate that the models can correctly identify most of the samples in both classes, with relatively low false-positive and false-negative rates. These findings highlight the potential of deep learning and transfer learning techniques for automated seed quality assessment and precision agriculture applications.

Despite the promising results, certain limitations should be considered. The **size and diversity of the dataset** may influence the generalization capability of the trained models. Variations in seed variety, lighting conditions, camera quality, background, orientation, moisture content, and disease severity may affect classification performance in real-world environments. Since the experiments were conducted under relatively controlled imaging conditions, the reported performance may not fully represent the challenges encountered during practical field-level deployment. Therefore, extensive validation using larger and more diverse datasets is necessary before deploying the system in real agricultural environments.

7. References

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