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Detection of Rice and Corn Plant Leaf Disease Using Invariants of Deep Learning Models and Edge Perspective

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Abstract: Rice and corn hold significant importance due to their daily consumption worldwide. Naked-eye observations are not accurate. Therefore, we need an autonomous system that can accurately detect and classify diseases in both plants. We trained and validated publicly available datasets in three deep convolutional neural network (DCNN)-based deep learning models using different learning rates and found that the lowest learning rate was the most effective in achieving the highest accuracy. We added a new dense layer to the known DCNN-based deep learning models and achieved improved accuracy. The best results were observed when our invariants of the InceptionV3, ResNet152, and MobileNetV2 deep learning models were used on corn plant leaves (98.09%, 98.51%, and 89.73%, respectively). These models also performed well on rice plant leaves (98.51%, 93.59%, and 98.57%, respectively). Because InceptionV3 performed well for both plants, we implemented it in NVIDIA Jetson Nano as an end device for the detection and classification of diseases from both plant leaves.

Keywords: deep learning, an invariant of Inception, InceptionV3, ResNet152, MobileNetV2, NVIDIA Jetson Nano, plant disease

1. Introduction

Rice and corn are important crops worldwide, serving as primary food sources for large populations. Monitoring the leaves for disease symptoms is an important part of maintaining the health of these crops. Leaf infections may have a substantial influence on plant development and productivity [1]. Therefore, it is important to recognize and address these concerns as soon as they arise. The position of the infection on the leaf and its specific features are key indicators of the crop's general health. Farmers and agricultural specialists may determine the severity and possible spread of a disease by studying its signs on the leaves, allowing them to take quick actions to limit any harmful impacts [2]. However, the incidence and severity of corn diseases [3] have increased over time. This increase is primarily due to changes in agricultural techniques [4], such as crop rotation [5] and monoculture [6], which can affect environmental conditions and microbial populations, influencing disease development. Furthermore, the introduction of novel pathogen strains and the deterioration of efficient plant protection techniques have aggravated the problem, resulting in increasingly frequent and serious outbreaks.

Eight common maize leaf diseases, namely, Curvularia leaf spot [7], predominate mosaic [8], dim leaf spot [9], northern leaf curse [10], earthy-colored spot [11], round spot [12], rust [13], and southern leaf scourge [14], pose serious threats to corn production. The symptoms of various diseases can vary greatly, making diagnosis difficult, especially for farmers without professional knowledge of plant pathology. Although skilled plant pathologists can frequently identify these diseases based on visual examination of the symptoms, uneducated farmers may fail to precisely diagnose the exact kind of infection, resulting in delayed or inefficient treatment.

Rice production is crucial for feeding a large portion of the global population, especially in areas where rice is a staple diet. However, infections caused by bacterial, viral, or fungal pathogens have a major impact on rice output. These diseases [15] have the potential to significantly reduce rice output, jeopardizing food security and farmer livelihoods. As a result, early and precise detection of rice leaf diseases is crucial for sustaining high rice output and satisfying worldwide demand. Factors such as image backdrop and capture settings can affect various visual symptoms, making the detection of rice leaf diseases difficult [16]. These variances [17] make it challenging to create robust models capable of reliably identifying diseases in a variety of habitats and imaging situations. Traditional disease recognition methods frequently rely on manual examination, which is time-consuming, error-prone, and dependent on the observer's experience. Infected and healthy leaves of rice and corn are shown in Figure 1.

Advances in technology, particularly deep learning [18], have created new opportunities for properly recognizing and diagnosing plant diseases. These approaches enable the analysis of plant leaf images to detect particular diseases. In agriculture, the ability to differentiate between different types of diseases using indicators found in leaf images is becoming a more significant tool. We developed deep learning models using modern image recognition techniques to accurately and quickly identify and classify maize and rice leaf diseases. Several datasets are used to train these algorithms to identify specific visual characteristics associated with each type of disease.

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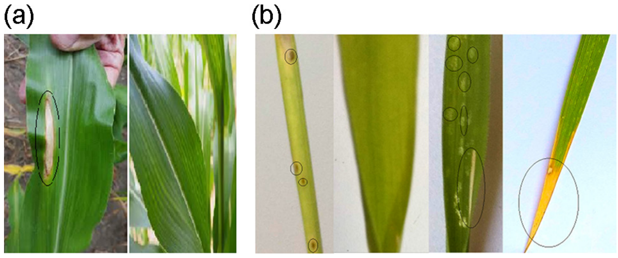
Figure 1
(a) Corn leaves of infected and healthy samples and (b) rice leaves of blight, healthy, brown spots, and leaf smut samples



Convolutional neural networks (CNNs) [19], a deep learning model famous for its performance in image identification tasks, have emerged as an important area of research in rice and corn leaf disease identification because of their capacity to automatically learn and extract essential information from images. We can use these characteristics to identify and diagnose various forms of leaf diseases. However, despite their effectiveness, CNN-based models frequently encounter constraints when applied to independent datasets. One of the most significant concerns is that these models perform poorly when applied to data that differ from the training set in terms of image backgrounds and capture settings. This decrease in identification rates is a significant challenge because it restricts the models' generalizability and practical applicability in real-world circumstances.

Furthermore, standard deep CNN (DCNN) models [20] necessitate large-scale networks with multiple parameters, making them computationally expensive and challenging to implement on devices with limited resources. To address this issue, we developed a novel CNN-based model for rice and corn leaf disease classification that reduces parameter complexity while maintaining accuracy. Importantly, we used our model in NVIDIA Jetson Nano, a compact and cost-effective edge device widely adopted for AI applications in field environments, to demonstrate its practical usability. By optimizing our model for Jetson Nano, we ensure real-time, offline inference capabilities, which makes the solution suitable for rural and low-resource agricultural settings where access to cloud computing is limited. This hardware-oriented deployment underscores the real-world relevance and scalability of our work, which extends the benefits of AI to on-field plant disease monitoring systems.

The remainder of this paper is organized as follows: Section 2 discusses related work, Section 3 presents the details of our methodology, Section 4 showcases the results and their brief discussion, and Section 5 provides the conclusion and possible future recommendations.

2. Literature Review

Advancements in deep learning techniques have significantly improved the field of plant disease classification because several studies have demonstrated the effectiveness of various neural network architectures. This section presents a concise summary of the research, focusing on the primary methods, datasets, and challenges faced using deep learning to detect plant diseases. Tables 1 and 2 provide a concise overview of the deep-learning approaches used to classify plant diseases.

2.1. Related work

Several studies have demonstrated the potential of deep learning models, particularly DCNNs, in automating the detection of crop diseases. For example, Singh et al. [21] proposed a custom CNN architecture to classify four common rice plant diseases while

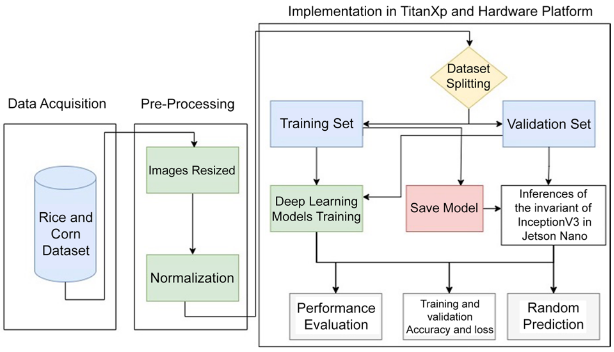
Table 1
Deep learning approaches used for the classification of rice plant disease

Author and Publication year	Dataset	Source of Data	Deep Learning Classifier	Accuracy
Singh et al. [21]	Rice Plant Diseases	From Rice Fields in Western Orissa, India	Customize CNN	99.66%
	Healthy Rice Leaf Dataset	From the Imphal East District, Manipur, India		99.83%
Agrawal et al. [24]	Rice Plant Diseases	Kaggle dataset	VGG19	97.25
			SqueezeNet	96%
			CNN	95%
			ResNet50	97.5%
			XceptionNet	96.5%
Kaur et al. [31]	Pooled Dataset	Mendeley and Kaggle datasets	SqueezeNet	93.3%
			VGG16	91.4%
			InceptionV3	93.1%
Bathe et al. [32]	Integrated and Custom dataset	Mendeley, UCI, and Kaggle dataset	CNN	90.29%
			DS-CNN	89.28%
			InceptionV3	99.46%
			MobileNetV2	80.25%
			Xception	99.2%
			TransEnsembleNet	98.73%
			ConvDepthTransEnsembleNet	99.33%

Table 2
Deep learning approaches used for the classification of corn plant disease

Author and Publication year	Dataset	Source of Data	Deep Learning Classifier	Accuracy
Pratama et al. [22]	Corn Plant Diseases	Kaggle dataset	AlexNet	75.87%
			LeNet	80.87%
			MobileNet	83.37%
Abas et al. [23]	Corn Plant Diseases	Kaggle dataset	CNN	99%
			AlexNet	93.5%
			VGG16	95.63%
Saleh et al. [26]	Corn Plant Diseases	Kaggle dataset	CNN	99.8%
			SVM	99.11%
Salihu et al. [27]	Corn Plant Diseases	Mendeley.com	CNN (With Data Augmentation)	95.53%
Rajeena PP et al. [28]	Corn Leaf Diseases	PlantVillage and PlantDoc	EfficientNetB0	98.85%
Elmasry et al. [30]	Corn Leaf Diseases	PlantVillage and PlantDoc	DenseNetDNN	96.1%

Figure 2
Block diagram of the proposed methodology



minimizing network parameters. Their experiments, conducted using stochastic gradient descent with momentum (SGDM) and Adam optimizers, achieved classification accuracies as high as 99.83%. However, despite these strong results, the model's applicability was limited to controlled datasets, with no mention of deployment constraints or generalizability to real-world, handheld platforms. Expanding on this direction, Pratama et al. [22] focused on maize disease classification using a Kaggle dataset. They compared several standard architectures, such as AlexNet, LeNet, and MobileNet, and found that MobileNet provided superior results with an accuracy of 83.37%. Although their work offered insights into model benchmarking, it did not explain how model size and inference speed would affect practical deployment, particularly on edge devices.

In line with the need for model optimization, Abas et al. [23] conducted a systematic literature review (SLR) on CNN-based corn disease detection, emphasizing the importance of hyperparameter tuning. Their findings highlight that parameter selection in each convolution layer substantially affects classification performance. However, they note a clear research gap: most studies do not experimentally validate the effect of such hyperparameter optimization, leaving performance gains mostly theoretical. To address limitations in training strategies, Agrawal et al. [24] employed both baseline and transfer learning methods with various architectures, including VGG19, ResNet50, and DenseNet. Their results confirmed ResNet50's superiority with a 97.5% accuracy. However, their model evaluation focused on accuracy alone, without considering inference latency or model size, which are two crucial aspects for real-time, on-device classification, which our work directly addresses.

Continuing the exploration of backbone architectures, Mizan et al. [25] used EfficientNet-B3 to identify diseases in staple crops such as rice and maize, reaching high accuracies across all categories. However, the study does not examine model efficiency in confined computing environments such as edge platforms, which limits its practical applicability. Saleh et al. [26] demonstrated the importance of model interpretability and dataset augmentation when they compared CNN to support vector machines (SVMs) and discovered CNN to be superior in maize disease diagnosis. The study emphasized data augmentation and consistent training parameters. Still, it left gaps concerning real-world implementation and user interpretability, which we expressly address in our suggested approach using lightweight architectures and hardware testing.

To increase real-world durability, Salihu et al. [27] used data augmentation techniques and found that CNNs attained a classification accuracy of 95.53% when trained on altered images. Although this study emphasizes the importance of better training data, the model has yet to be validated in real-world settings. Our technique expands on this by using the model in Jetson Nano and testing its performance in uncontrolled situations. Rajeena PP et al. [28] investigated the application of sophisticated feature extractors, implementing EfficientNet and DenseNet designs with high precision and recall. Their technique optimized various hyperparameters for better classification but did not consider deployment practicality, such as the models' energy efficiency or memory limits on mobile platforms.

To improve generalizability, Barman et al. [29] developed a hybrid model that combines EfficientNetB0 and SVMs. Although the model produced competitive results across many crops and diseases, its dependence on computationally costly structures limits real-time field deployment—a barrier that our study addresses by employing optimized, lightweight CNN variations. Elmasry et al. [30] improved hybrid designs by proposing DenseNetDNN, a combination of DenseNet121 and deep neural networks that performs well on corn disease detection. However, although correct, their method was not tested on any edge platform or in a real-world deployment situation. In contrast, we specifically construct and assess models in Jetson Nano to ensure real-time responsiveness.

Kaur et al. [31] used an ensemble-based technique to identify rice leaf disease by merging feature extractors VGG16, InceptionV3, and SqueezeNet. Their model achieved 93.3% accuracy, but model complexity and a lack of deployment considerations remain significant limits. To overcome this, we immediately integrate the best-performing model variation into an embedded system context. Bathe et al. [32] expanded on this idea by creating a weighted ensemble model, ConvDepthTransEnsembleNet, which obtained 96.88% accuracy on a small, unbalanced dataset. Although impressive, the model's incredible complexity and processing expense make it unsuitable for portable or field-based use, which is precisely the scenario addressed in our suggested implementation.

Recent advances in infrared object detection have been propelled by innovations in feature extraction and adaptation across modalities. Deep-IRTarget introduced a dual-domain feature extraction mechanism, combining spatial and frequency domain information to significantly enhance target detection accuracy in infrared imagery [33]. Building on this, the Differential Feature Awareness Network incorporated antagonistic learning [34] to further improve detection in cross-domain (infrared–visible) scenarios by emphasizing differential feature extraction and allocation. To address the challenge of limited annotated data, a benchmark and frequency compression method for infrared few-shot object detection established the IFSOD benchmark and proposed frequency compression techniques, facilitating robust few-shot learning in complex infrared environments [35]. Collectively, these works establish a strong foundation for future research in robust and data-efficient infrared object detection, especially in applications where annotated data are scarce and cross-domain generalization is crucial.

2.2. Gap analysis

The literature study reveals notable progress in using CNNs for identifying and categorizing plant diseases, specifically in major crops such as rice, maize, and corn. Despite the progress, specific gaps remain unaddressed. These gaps provide prospects for additional research to implement the CNN in an edge platform as a handheld solution. Dataset diversity is a topic that requires further consideration. Moreover, the CNN models have limited interpretability, which challenges end-users, such as farmers, to have confidence in and comprehend the predictions. There is a deficiency in the practical implementation of these models because several studies concentrate on controlled settings. Our proposed methodology addresses all mentioned issues and provides the best solution. The proposed research paper delves deeper into our contributions, and here is the summary:

1) We added a dense layer to deep learning models InceptionV3, ResNet152, and MobileNetV2 and improved their accuracy on publicly available datasets of rice and corn.
2) We compared the performance of deep learning models using different learning rates, demonstrating the importance of hyperparameters for models' performance.
3) We compared results with the invariant of InceptionV3, ResNet152, and MobileNetV2 and found promising results compared with the latest research.
4) We have implemented the invariant of InceptionV3 in Jetson Nano as a handheld solution for disease detection and classification in rice and corn plants.

In the following sections of the proposed paper, we will delve into the methodology of our proposed technique, discuss the experimental setup, discuss the achieved results in both software and hardware, and conclude with potential future directions.

3. Proposed Methodology

3.1. Dataset acquisition and distribution

The dataset used in this study was obtained from Kaggle, comprising images of corn and rice. For the rice dataset, a total of 16,000 images were obtained, with an equal distribution of 4,000 images across four classes: bacterial leaf blight, brown spot, healthy, and leaf smut. These images were divided into training and testing datasets, with 70% allocated for training and 30% for testing. Similarly, the corn dataset, consisting of 4,546 images, was also divided into 70% for training and 30% for testing. The corn dataset included two classes: 2,567 healthy images and 1,979 infected images. Table 3 below illustrates the dataset distribution.

3.2. Preprocessing

Preprocessing is a crucial step in image processing as it enables the normalization of pixel values and the resizing of images. In this work, preprocessing was conducted to resize and normalize the images. The original image dimensions were 512 × 512 × 3, which were resized to 256 × 256 × 3. Equation (1) was used for resizing the images.

$$\mathrm{T_x} = \frac{\text{new width}}{\text{original Width}}, \mathrm{T_y} = \frac{\text{new height}}{\text{original Height}} \tag{1}$$

For each pixel in the resized image, the corresponding pixel in the original image is calculated as in Equation (2):

$$x_{\text{orig}} = \frac{x_{\text{new}}}{T_x},\ y_{\text{orig}} = \frac{y_{\text{new}}}{T_y} \tag{2}$$

where (x_{new}, y_{new}) are the coordinates in the resized image and (x_{orig}, y_{orig}) are the corresponding coordinates in the original image.

Depending on the interpolation method, ↓ pixel value at (x_{new}, y_{new}) is computed using the pixel values around (x_{orig}, y_{orig}) in the original image. These resize frames are used for normalization of frames. Normalization is used to scale the image in a specific range, such as [0,1]. In this study, we applied image normalization to scale the pixel values to a specific range. The equation used for this normalization is provided in Equation (3).

$$\mathrm{N} = \frac{\text{pixel value} - \min}{\max - \min} \tag{3}$$

where N represents the normalized values obtained after applying normalization. The term pixel value refers to the original pixel value, which ranges from 0 to 255 in an 8-bit image. Min denotes the minimum

Table 3
Dataset distribution among different classes of rice and corn plant leaves

	Rice		Corn	
Serial No.	Class Type	No of Images	Class Type	No of Images
1	Bacterial leaf blight	4000	Healthy	2567
2	Brown spot	4000	Infected	1979
3	Healthy	4000	-	-
4	Leaf Smut	4000	-	-
	Total	16000	Total	4546

possible value, typically 0, whereas Max refers to the maximum possible value, typically 255. Preprocessing is also demonstrated in Figure 2, along with a broader overview of the proposed methodology.

3.3. Invariants of deep learning models

3.3.1. Deep learning feature extraction

In the rice and corn image classification task, invariants of deep learning models were used because of their superior performance compared to traditional classification techniques. The architecture of a simple CNN model used for classification is detailed below. Figure 3 shows the generic architecture of the CNN model.

Convolution Layer: Local features are extracted through the convolutional layers as the data passes from the input layer. Equation (4) is used for the mathematical expression.

$$RI^{L} = (\mathrm{I}_{x\times x} + \mathrm{W}_{x\times x}) + S \tag{4}$$

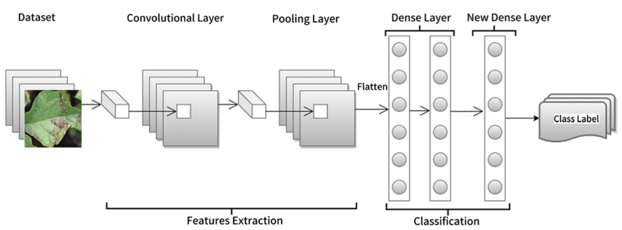
Here, $I_{x\times x}$ represents the input data, and $W_{x\times x}$ denotes the weight vector. The variable x signifies the kernel and filter size, and S represents the bias factor. These are then passed to an activation layer to address the nonlinearity among the features.

Max-Pooling Layer: The max-pooling layer segments the feature map into smaller, nonoverlapping pooling kernels. It selects the maximum value from each kernel and passes it to the subsequent layer. This layer involves two primary functions: (1) downsampling the data from the previous layer to reduce its dimensionality and (2) enhancing model parameters and decreasing computational time.

Fine-Tuned ResNet152: The residual network (ResNet) is a deep learning model characterized by its use of skip connections between layers, which helps in preserving knowledge, reducing loss, and improving performance during the training phase. ResNet was originally trained on the ImageNet dataset, which consists of 1,000 classes. For our work, we fine-tuned a ResNet152 model for a classification task. Specifically, we replaced the original fully connected layer with a new layer and then applied transfer learning to train the model. During training, several hyperparameters were used: a mini-batch size of 8, a learning rate of 0.0001, 100 epochs, and the mean squared error loss function. The optimizer used was gradient descent, and average pooling followed by activation was employed for feature extraction.

Fine-Tuned InceptionV3: The fine-tuned InceptionV3 model is a deep learning classification model used in our work for the task of rice and corn classification. Similar to ResNet152, InceptionV3 was initially trained on the large-scale ImageNet dataset, which comprises 1,000 classes. For our specific task, we fine-tuned the InceptionV3 model. This involved first removing the original fully connected layer, adding an additional dense layer to the model, and then incorporating a fine-tuned fully connected layer. Finally, pooling and activation functions were applied to the features to complete the model's architecture.

Figure 3
Convolutional neutral network (CNN) with a new dense layer



Fine-Tuned MobileNetV2: MobileNetV2 is a deep learning model that employs residual connections and separable convolutions to enhance performance. In our work, we used a fine-tuned MobileNetV2 architecture for the classification of rice and corn diseases. The MobileNetV2 model begins with an initial fully connected layer with a filter size of 32, followed by 19 residual layers. ReLU is used for nonlinearity, with a standard 3 × 3 kernel, along with dropout and normalization during the training phase. Except for the fully connected layer, the original architecture remains unchanged. The original fully connected layer was replaced with a fine-tuned layer tailored for the classification task of rice and corn diseases, followed by ReLU and pooling layers. Several hyperparameters were adjusted to achieve the desired accuracy and performance, including a learning rate of 0.0001, a batch size of 8, cross-entropy as the loss function, and gradient descent as the optimizer. The network consists of 3.4 million parameters. To improve the robustness and performance of the model, an additional dense layer was incorporated.

3.4. Classification

Fully Connected Layer: Logical inference is performed by the fully connected layer, which transforms a 3D matrix into a 1D vector through fully connected operations, as shown in Equation (5).

$$Z_{y_0 X_1} = \text{weight}_{yoX_{zj}} \cdot X_{z_j x_1} \cdot A_{zo,X1} \tag{5}$$

where the input and output vector sizes are represented by y_o and Z_j and Z is the output of the FC layer.

Dense Layer: A dense layer is a fully connected layer. Instead of adding two dense layers, we add an additional dense layer before the softmax layer. This extra layer enables the model to learn more abstract features, refining the representations before reaching the softmax layer.

Softmax Layer: In the architecture of the CNN, this layer functions as the classification layer, responsible for determining the probabilities of the output and normalizing the class predictions. $b(x^{(j)}=m' \mid y^{(j)}; X)$, as expressed in Equation (6).

$$\left(x^{(j)} = m' \,\middle|\, y^{(i)}; X\right) = \begin{bmatrix} \left(x^{(i)} = 1 \,\middle|\, y^{(i)}; X\right. \\ \left(x^{(i)} = 2 \,\middle|\, y^{(i)}; X\right. \\ . \\ . \\ \left(x^{(i)} = m \,\middle|\, y^{(i)}; X\right. \end{bmatrix} = \frac{1}{\sum_{i=j}^{m} v^{x^{i}}{}_{iy^{(i)}}} \begin{bmatrix} v^{x^{i}_{i}} y^{(i)} \\ v^{x/2} y^{(i)} \\ . \\ . \\ v^{x^{ij}_{ij}} y^{(i)} \end{bmatrix} \tag{6}$$

where z is the number of samples = 1, m represents the weights that are replaced by X, and the input of the classifier is $v^{x^{i}_{i}} y^{(i)}$.

3.5. Hardware platform Jetson Nano implementation

We used the invariant of InceptionV3 because of its superior performance, which was selected for hardware deployment. Prior to deployment, the model was optimized using TensorRT. Figure 4 illustrates the deployment of the models using PyTorch on a PC, and Figure 5 demonstrates the deployment of InceptionV3 on the Jetson Nano platform.

PyTorch to TRT: Torch-TensorRT converts PyTorch models into TensorRT engines optimized for deployment on NVIDIA GPU

Figure 4
Model training using PyTorch on GPU

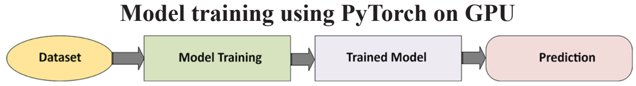
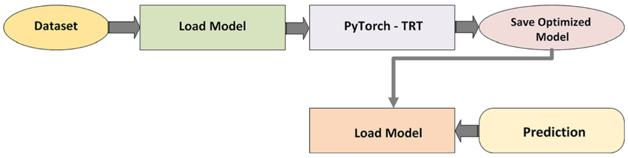


Figure 5
Model deployment on edge platform using PyTorch-TRT



platforms. This high-performance deep learning optimizer uses mathematical operations to transform PyTorch models into TensorRT format, enhancing performance while maintaining accuracy. TensorRT uses the ONNX graph to convert models into TensorRT format, as shown in Equation (7), optimizing each operation during the conversion process.

$$X_{\text{TensorRT}} = \text{parse}\left(X_{\text{ONNX}}\right) \tag{7}$$

Layer Fusion and Optimization: TensorRT employs optimizations such as layer fusion, where sequences of convolutional layers are combined into a single unit to reduce memory usage and computation time.

Convolution layers with operation y=θ*x+c and a ReLU activation z=max(0,y) are required. TensorRT may fuse these into a single optimized operation, as shown in Equation (8):

$$b = \max(0, \theta^{*}x + c) \tag{8}$$

Precision Calibration and Quantization: TensorRT employs precision operations to convert 32-bit floating-point values to 8-bit floating-point values, thereby enhancing performance. It also uses quantization techniques to minimize any loss of accuracy during this process.

Quantization can be applied to map a high-precision value x to a lower-precision value x_m using a scale factor s and an offset L expressed in Equation (9).

$$x_m = \text{round}\left(\frac{x}{s} + L\right) \tag{9}$$

Kernel Section and Optimization: TensorRT optimizes performance by selecting the most efficient implementation for the target hardware, choosing kernels that minimize memory usage, bandwidth, and computation time. For convolution y=θ*x+c, TensorRT may employ different methods, such as direct convolution or FFT, depending on which is best suited to the input size and hardware.

Pruning and Tensor Memory Management: TensorRT prunes unnecessary neurons and manages memory to enhance runtime throughput using pruning, as shown in Equation (10). Memory optimization is achieved by efficiently allocating and deallocating resources as needed.

$$X' = \text{Prune}\left(X\right) \tag{10}$$

After this step, the model is serialized into a format that can be directly loaded onto the target hardware. This format is designed to be lightweight and fast loading.

$$\text{Model}_{\text{TensorRT}} = \text{Serialize}\left(G_{\text{TensorRT}}\right) \tag{11}$$

The process of converting PyTorch models to TensorRT involves exporting the model to ONNX, parsing it, applying techniques such as layer fusion and quantization, and finally serializing it for deployment. This process uses practical optimizations to minimize inference time on hardware as expressed in Equation (11).

4. Results and Discussions

4.1. Experimental setup

This study was conducted using NVIDIA Quadro P5000. It has a dedicated GPU of 16 GB with a process speed of up to 4.0 GHz, which ensures optimal functionality of the computer hardware and software components. We created a separate virtual environment for the proposed approach and a comparison of different DL models. PyTorch framework was used for InceptionV3, ResNet152, and MobileNetV2 and their invariants.

Similarly, Jetson Nano has 4 GB of LPDDR4 RAM, which allows us to handle multiple DL models. It also includes 16 GB of eMMC storage, an expandable via microSD, providing flexibility for storage needs. The device offers various I/O options, including USB 3.0, HDMI, MIPI CSI-2 camera interfaces, and a Gigabit Ethernet port, enabling seamless integration with sensors, cameras, and other peripherals. We used it for the optimization and deployment of the invariant of the InceptionV3 DL model for real-time edge implementation.

4.2. Results and discussions

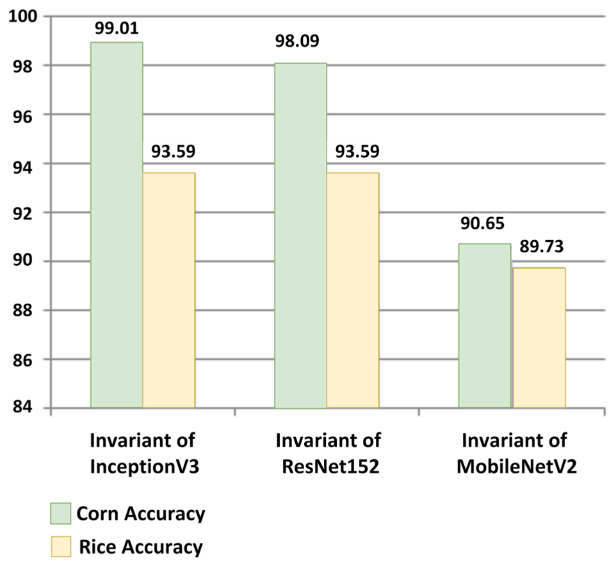
Table 4 shows the impact of different learning rates on the accuracy of these models. It is evident that as the learning rate decreases, the accuracy tends to improve, particularly at a learning rate of 0.001, where the InceptionV3 model reaches a peak accuracy of 99.13% for corn leaves and 97.39% for rice leaves. This trend is similarly observed in ResNet152, which achieves 92.60% accuracy for corn and 91.39% for rice at the same learning rate. MobileNetV2, though less accurate overall, still shows improvement with reduced learning rates, although its performance plateaus at approximately 88% for both corn and rice leaves. These data highlight the significance of fine-tuning learning rates to optimize model performance in agricultural classification tasks.

Figure 6 and Table 5 provide insights into the accuracy of different deep learning models, i.e., InceptionV3, ResNet152, and MobileNetV2, when applied to the classification of rice and corn

Table 4
Accuracy of DL models through different learning rates

Model	InceptionV3 Accuracy (%)				ResNet152 Accuracy (%)				MobileNetV2 Accuracy (%)			
Learning rate	0.1	0.01	0.001	0.0001	0.1	0.01	0.001	0.0001	0.1	0.01	0.001	0.0001
Corn accuracy	72.72	89.70	99.13	98.71	65.33	87.98	92.60	96.89	69.71	83.31	88.05	88.09
Rice accuracy	74.41	85.41	97.39	97.40	61.11	88.23	91.39	91.29	73.31	86.19	87.44	87.46

Figure 6
Accuracy bar graph using invariants of deep learning models for rice and corn leaves



leaves. The figure shows the performance of these models using invariant features, where the InceptionV3 model achieves the highest accuracy for both corn and rice leaves, with 99.01% and 93.59%, respectively. ResNet152 also demonstrates strong performance, particularly for corn leaves with an accuracy of 98.09%, slightly lower than that of InceptionV3. However, the accuracy decreases to 89.73% for rice leaves when using MobileNetV2, indicating a relatively lower performance compared to the other models.

Table 5 highlights the impact of different learning rates on the performance of the invariant models. The invariant of InceptionV3 demonstrates the highest accuracy, reaching 99.01% for corn and 98.51% for rice at an optimal learning rate of 0.0001. Similarly, the invariant of ResNet152 also shows significant accuracy improvements at lower learning rates, particularly achieving 98.09% for corn and 93.59% for rice. MobileNetV2, though generally less accurate than the other models, still benefits from lower learning rates, with its accuracy peaking at 90.65% for corn and 89.73% for rice.

The results in Table 6 clearly demonstrate that incorporating invariant layers or mechanisms into deep learning architectures substantially boosts the accuracy and reliability of crop disease detection models. The overall accuracy graph for rice and corn is shown in Figure 7 to analyze the performance of the deep learning model used in the study. The invariant of InceptionV3 stands out as the top performer, achieving near-perfect classification for both corn and rice disease images. ResNet152 and its invariant also show strong potential, especially for corn. Although MobileNetV2 offers a lightweight solution, its lower performance suggests that it may be less suitable for scenarios where high accuracy is crucial. Overall, the findings highlight the importance of both model architecture and the use of invariant techniques in achieving robust, generalizable results for real-world agricultural disease detection tasks. For practical deployment in precision agriculture, the invariant of InceptionV3 is recommended because of its superior performance across all evaluation metrics, ensuring both high accuracy and reliability in diverse field conditions.

Figure 8 shows the training and validation accuracy graphs for three models applied to rice and corn leaf classification. In subfigure A, the invariant of InceptionV3 for rice shows a steady increase in both training and validation accuracies, with the validation accuracy closely following the training accuracy, indicating a well-generalized model with minimal overfitting. Subfigure B, which represents the invariant of InceptionV3 for corn, shows a similar pattern showcasing the model's robustness and effectiveness in classifying corn leaves. Subfigure C, which shows the training and validation accuracies for the invariant of MobileNetV2 on corn leaves, shows a slightly different trend. Although

Table 5
Accuracy of invariants of deep learning models through different learning rates

Model	Invariant of InceptionV3				Invariant of ResNet152				Invariant of MobileNetV2			
Learning Rate	0.1	0.01	0.001	0.0001	0.1	0.01	0.001	0.0001	0.1	0.01	0.001	0.0001
Corn accuracy	86.74	91.75	98.93	99.01	66.51	89.88	94.65	98.09	70.51	83.81	90.65	90.51
Rice accuracy	76.42	87.21	98.30	98.51	63.91	89.78	93.55	93.59	73.71	83.81	89.73	89.73

Table 6
Comparison of deep learning models without VS with a dense layer having the best learning rates

	Corn				Rice			
Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
InceptionV3	98.71	98.61	98.42	98.51	97.40	97.42	97.39	97.38
Invariant of InceptionV3	99.01	98.94	99.00	98.99	98.51	98.39	98.34	98.49
ResNet152	96.89	96.83	96.56	96.93	91.39	91.41	91.99	91.29
Invariant of ResNet152	98.09	98.01	98.18	98.08	93.59	93.62	93.51	93.58
MobileNetV2	88.09	88.00	88.10	88.13	87.46	87.42	87.39	87.45
Invariant of MobileNetV2	90.65	90.64	90.59	90.63	89.73	89.69	89.63	89.74

Figure 7
Accuracy bar graph of deep learning models and their invariants for rice and corn leaves

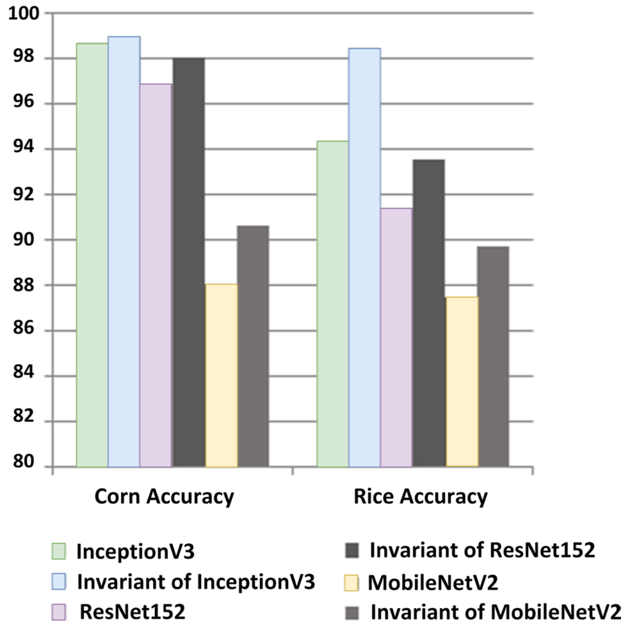
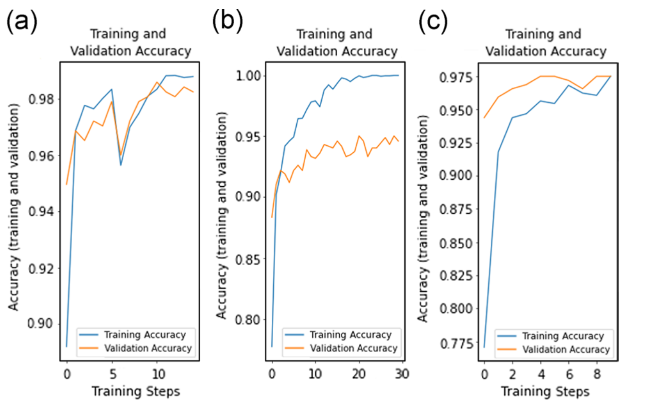


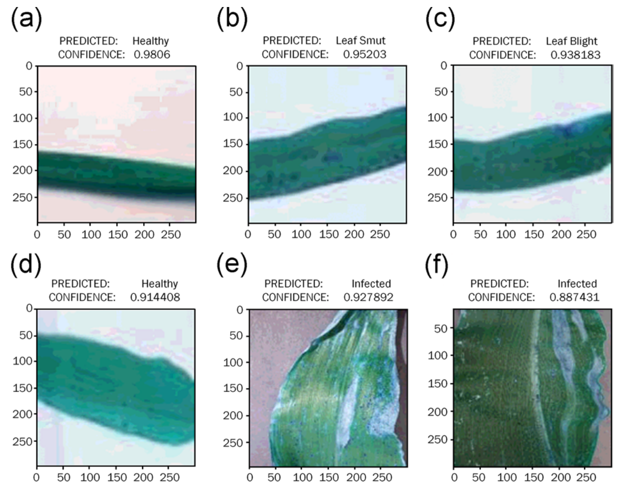
Figure 8
Training and validation accuracy graph of the (a) invariant of InceptionV3 for rice, (b) invariant of InceptionV3 for corn, and (c) invariant of MobileNetV2 for corn



both training and validation accuracies increase rapidly at the beginning, the validation accuracy plateaus, slightly below the training accuracy. This suggests that although the model is performing well, there is a small gap between the training and validation accuracies, indicating potential overfitting or a need for further fine-tuning. Overall, these graphs underscore the effectiveness of the invariants of InceptionV3 in both rice and corn classification tasks, with MobileNetV2 also performing competitively but with a need for slight adjustments.

A shown in Figure 9, the system predicts the health status of rice and corn leaves using different deep learning models, specifically invariants of InceptionV3, ResNet152, and MobileNetV2. The predictions cover various conditions such as healthy, leaf smut, leaf blight, and infected leaves. The models demonstrate high confidence levels, mostly above 0.90, indicating a strong ability to distinguish between healthy and diseased leaves. Each model variant shows consistent performance, particularly in correctly identifying the disease

Figure 9
Random prediction of the system: (a) invariant of InceptionV3 for rice leaf, (b) invariant of ResNet152 for rice leaf, (c) invariant of MobileNetV2 for rice leaf, (d) invariant of InceptionV3 for corn leaf, (e) invariant of ResNet152 for Corn Leaf, and (f) invariant of MobileNetV2 for corn leaf



states in rice and corn leaves, which suggests that the models are well suited for agricultural disease diagnosis.

Figure 10 shows the predictions of the NVIDIA model using an invariant of the InceptionV3 architecture for both rice and corn leaves. The figure includes predictions for healthy and infected leaves of both crops. The model again shows high confidence in its predictions, similar to the results in Figure 9. This consistency across different models and architectures highlights the robustness of deep learning approaches in plant disease detection, particularly when using sophisticated models such as InceptionV3. The model's ability to accurately classify healthy and diseased leaves from different crops underscores its potential application in precision agriculture.

Table 7 presents a comprehensive comparison between recent state-of-the-art methodologies and our proposed deep-learning-based invariant models for rice and corn disease classification. The table highlights the accuracy achieved by various methods, including traditional machine learning algorithms (such as SVM and Random Forest), classical CNNs, and more advanced architectures such as ResNet50, EfficientNet, and MobileNetV2.

For rice disease classification, previous studies have reported accuracies ranging from 92.8% (SVM by Seelwal et al. [36]) to 97.5% (EfficientNet by Li et al. [16]). Similarly, for corn disease classification, the highest reported accuracy among prior works is 96.3% (CNN by Kim et al. [37]), with other methods such as SVM, Random Forest, Multi-Layer Perceptron, and Decision Tree achieving slightly lower results. In contrast, our proposed methodologies, particularly the invariant of InceptionV3 and invariant of ResNet152, demonstrate a significant leap in performance. For rice, our models achieve accuracies of 98.51% and 93.59%, respectively, and for corn, the accuracies reach 99.01% and 98.09%. This marked improvement underscores the effectiveness of our deep learning architectures, especially the incorporation of invariant features, in capturing the complex patterns associated with crop diseases under real-world conditions.

The superior performance of our models can be attributed to several factors. First, the use of deep learning enables automatic extraction of hierarchical features, which are more robust to variations in lighting, background, and disease manifestation compared to

Figure 10
Random prediction of NVIDIA using the invariant of InceptionV3: (a) healthy rice leaf, (b) rice leaf blight, (c) healthy corn leaf, and (d) corn infected leaf

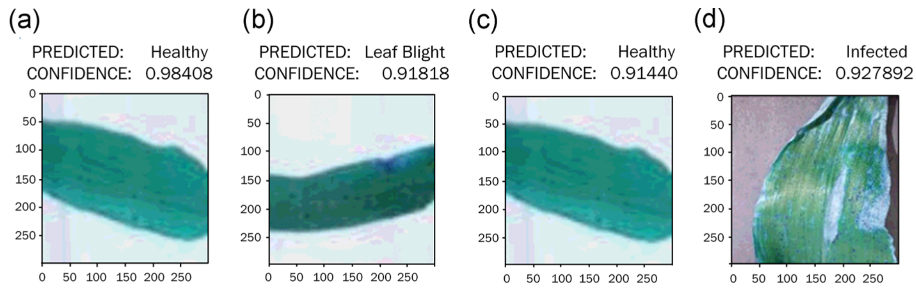


Table 7
Accuracy comparison of state-of-the-art methodologies versus our proposed methodology

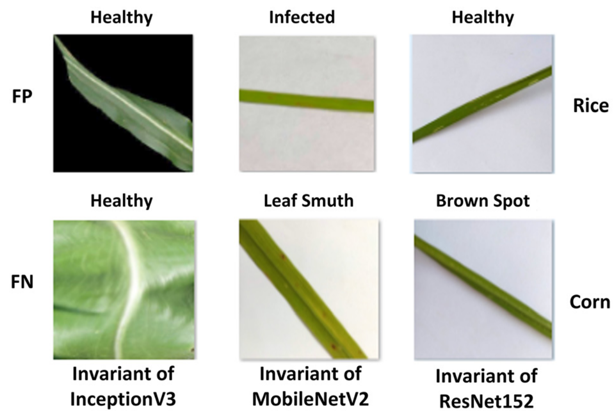
Contribution	Methodology (Rice)	Accuracy (%) (Rice)	Contribution	Methodology (Corn)	Accuracy (%) (Corn)
Lu et al. [38]	CNN	94.2	Patel et al. [43]	SVM	95.8
Rani & Singh [39]	ResNet50	96.7	Mishra et al. [44]	CNN	96.3
Duong et al. [40]	EfficientNet	97.5	Chauhan et al. [45]	Random Forest	93.6
Zaw et al. [41]	SVM	92.8	Li & Tanone [46]	Multi-Layer Perceptron	94.1
Liu et al. [42]	MobileNetV2	96.1	Verma & Dubey [47]	Decision Tree	92.7
Our (Invariant of InceptionV3)	Deep Learning	98.51	Our (Invariant of InceptionV3)	Deep Learning	99.01
Our (Invariant of ResNet152)	Deep Learning	93.59	Our (Invariant of ResNet152)	Deep Learning	98.09

handcrafted features used in traditional methods. Second, the invariant mechanisms integrated into our models enhance their ability to generalize across diverse image conditions, making them particularly suitable for field deployment where environmental variability is high. Moreover, the consistent outperformance of our models over recent literature not only establishes a new benchmark for accuracy in rice and corn disease classification but also demonstrates the practical potential of our approach for precision agriculture. By achieving near-perfect classification rates, our methodology can facilitate timely and accurate disease diagnosis, ultimately contributing to improved crop management and yield.

Figure 11 shows examples of false positive (FP) and false negative (FN) cases when using invariants of deep learning models (InceptionV3, MobileNetV2, and ResNet152) for rice and corn leaf disease detection. The FP samples show healthy leaves mistakenly identified as infected, whereas the FN samples display infected leaves incorrectly classified as healthy.

For rice leaves, the false positive and false negative cases are displayed for both the InceptionV3 and MobileNetV2 models. The false positives, particularly from the invariant of InceptionV3, show that even advanced models can mistakenly classify a healthy leaf as diseased, indicating the difficulty in distinguishing subtle features. Similarly, the false negatives highlight that some disease features are not always easily detected, leading to an incorrect healthy classification. For corn leaves, the invariant of ResNet152 demonstrates similar challenges, with misclassifications evident in both FP and FN categories, emphasizing the ongoing need to improve the precision and robustness of these models to reduce such errors.

Figure 11
Samples having false positive (FP) and false negative (FN) using invariants of deep learning models for rice and corn leaves



5. Conclusion

Deep learning methods are being used in many challenging tasks for autonomous classification, detection, and segmentation. In our study, we trained and validated publicly available datasets using three DCNN-based deep learning models with varying learning rates, discovering that the lowest learning rate yielded the highest accuracy. By incorporating a newly designed dense layer into the existing CNN architectures, we achieved significant improvements in classification accuracy. The most notable results were obtained using our invariants of the InceptionV3, ResNet152, and MobileNetV2 models on corn leaves. Similarly, these models performed exceptionally well on rice leaves as well. Given its consistently high performance across both crops, the InceptionV3 model was used in NVIDIA Jetson Nano as an end device for real-time disease detection and classification.

Although the results are promising, further research is recommended to enhance the robustness of these models under varying environmental conditions and across different plant varieties. In addition, expanding the dataset to include more disease types and stages could improve model generalization. Implementing these models in a broader range of hardware platforms and integrating them into a user-friendly interface can facilitate adoption among farmers and agricultural professionals, particularly in resource-limited settings [48].

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/vbookshelf/rice-leaf-diseases and https://www.kaggle.com/datasets/smaranjitghose/corn-or-maize-leaf-disease-dataset.

Author Contribution Statement

Zubair Saeed: Conceptualization, Methodology, Software, Validation, Resources, Data curation, Writing – original draft, Project administration. **Uzma Nawaz:** Validation, Formal analysis, Writing – review & editing. **Ali Raza:** Conceptualization, Validation, Formal analysis, Writing – review & editing, Visualization. **Kamran Javed:** Validation, Formal analysis, Investigation, Writing – review & editing, Visualization, Supervision.

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