Deep Learning Based Paddy DiseaseClassification Using Resnet-50

Thamarai selvi S B[1], Thirumurugan S[2], Kanish P[3], Surya M[4]

{thamaraiselvi@ksrct.ac.in[1], thirumurugan8465@gmail.com[2], kanishkumar022@gmail.com[3],suryasiva1503@gmail.com[4] }

Assistant Professor of Computer Science and Engineering, K S Rangasamy College of Technology, Tiruchengode, India[1], Student of Computer Science and Engineering, K S Rangasamy College of Technology, Tiruchengode, India[2,3,4]

Abstract. In this research, a Convolutional Neural Network (CNN) utilizing the ResNet-50 architecture is presented, demonstrating a noteworthy accuracy level of 97% in the classification of paddy diseases. By curating an extensive dataset of paddy disease images, employing data augmentation techniques, and tailoring the model, a practical tool for efficient disease detection and management in agriculture has been developed. The model's performance is further enhanced through a fine-tuning process that involves adjusting the learning rates of specific layers. This research not only underscores the potential of deep learning within the realm of agriculture but also contributes a valuable resource for farmers and agronomists. It provides them with a timely and precise means of paddy disease identification, ultimately leading to improved crop yields and the mitigation of losses.

Keywords: Deep Learning, Convolutional Neural Network, Paddy, Disease Detection, Agriculture.

1 Introduction

1.1 Paddy Disease Classification

Paddy disease classification is a crucial task in agriculture, employing advanced technology like Convolutional Neural Networks (CNNs) to identify and categorize various diseases affecting paddy plants, such as Brown Spot, Blast, and Bacterial Leaf Blight. This process starts with gathering a comprehensive dataset of paddy disease images, each tagged with its respective disease type. The model is fine-tuned to match the number of disease classes in the dataset, and iterative training with labelled images is carried out, with a portion of the data set aside for validation to ensure performance and prevent overfitting. The outcome is a trained model capable of accurately identifying paddy diseases in new, unseen images. Such models can greatly aid farmers and agriculture experts by offering timely disease diagnosis, facilitating swift intervention, and contributing to higher crop yields and sustainable farming practices. The

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primary goal of this research project is to create a highly accurate paddy disease classification system using a Convolutional Neural Network based on the ResNet-50 architecture, ultimately achieving an accuracy level of 97% to benefit farmers and agronomists.

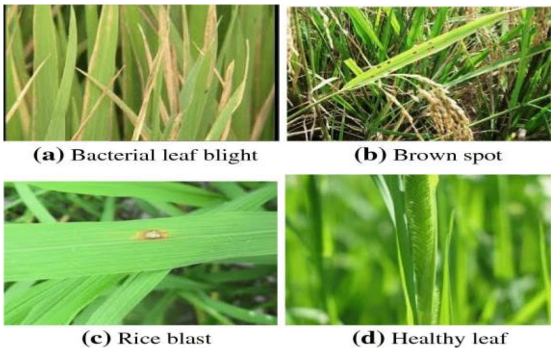

Fig. 1. Images of Paddy Leaves

In Figure 1, a visible illustration of paddy leaves is presented, showcasing both regular and diseased states. These example pictures shape the idea for the deep getting to know model, showing the intricacy and differences involved in the process of classifying paddy diseases.

1.2 Few-Shot Learning

Scarcely any shot learning is an AI worldview that tends to the difficult situation where a model necessity to make exact expectations or characterizations with exceptionally restricted models or information focuses per class. In customary AI, models frequently require a significant measure of marked information to successfully sum up. Nonetheless, hardly any shot gaining splits from this limitation by empowering models to gain from only a couple of models, normally one, five, or a tiny number, per class. The embodiment of few-shot learning [2] lies in its capacity to move information across errands or classes, making it especially helpful while managing novel, concealed classifications. These models figure out how to rapidly adjust to new undertakings by learning a generalizable portrayal of the information and catching the basic examples that can be applied to concealed classes.

2 Literature Survey

Serge Savary et al. [3] address crop-damaging microorganisms and pests, global food security threats, by collecting data on crop losses across crops and regions. Shivani Sood et al. [4] present an early detection method for rust diseases in wheat, a critical crop for India's winter wheat production. They classify plants as healthy or diseased, enhance image datasets, and employ ResNet50 and VGG16 models with fine-tuned hyperparameters. Charles Farber et al**.** [5] highlight the vital role of advanced diagnostics in potentially saving 50% of global agricultural yields by overcoming current limitations in plant disease detection. Yanfeng Zhao et al. [6] propose a novel approach using Double Generative Adversarial Networks (Double GAN) for imbalanced plant leaf disease datasets. They achieve remarkable accuracy of 99.80% for plant species recognition and 99.53% for disease identification. YAQING WANG et.al [7] stress the effectiveness of AI in data-rich scenarios and its limitations with small datasets. They introduce Few-Shot Learning (FSL), which uses prior knowledge to adapt to new tasks with limited data. Sunil S et.al [8] highlight the crucial role of farming in global food production and stress the importance of early plant disease detection, particularly in tomatoes. Imran Haider Khan et.al[9] introduce an early crop disease detection method using AI and hyperspectral imagery, departing from symptom-based approaches. Mohsen Azadbakht et.al [10] introduced an effective method for detecting wheat leaf rust, crucial for precision agriculture. They used spectral data to estimate disease severity accurately across various leaf area index (LAI) levels.

3 Existing System

The employment of a few-shot learnig approach in the wheat disease classification network, utilizing the Efficient Net architecture, showcases encouraging outcomes in tackling two pivotal challenges associated with the detection of diseases in wheat plants. It effectively identifies and classifies diseases, achieving a high accuracy rate of 93.19% when tested on 40 diverse images representing 18 different disease categories [1]. This demonstrates its capability even with a small dataset. Moreover, the fundamental Efficient Net model, as part of this network, achieved an accuracy of approximately 95.5% when evaluated using the CGIAR Dataset, highlighting its robust performance and computational efficiency. This superior performance, even with a reduced number of training image, underlines the model’s efficacy in overcoming the data and computational resource constraints often associated with deep learning-based disease detection systems.

4 Proposed Methodology

The proposed framework means to change how paddy illness characterization is done by utilizing cutting edge profound learning strategies. The framework is intended to give exact and opportune distinguishing proof of different paddy illnesses, offering huge advantages to the agrarian local area. At its centre, the framework utilizes a Convolutional Brain Organization (CNN) engineering, explicitly the ResNet-50 model which has exhibited excellent execution in picture order errands. This incorporates adjusting the model's last arrangement layer to match the quantity of unmistakable sickness classifications in the dataset. To guarantee the model's viability and heartiness, we cautiously curate an exhaustive dataset of paddy infection pictures, with each picture carefully marked with its comparing sickness type. Information pre-handling strategies are utilized to normalize and expand the dataset, permitting the model to sum up better and make exact expectations even within the sight of varieties in picture quality and conditions. The framework integrates progressed information increase techniques to upgrade the model's capacity to gain from a set number of preparing models, successfully tending to the couple of shot learning challenge. During the preparation interaction, a part of the dataset is held for approval to screen the model's exhibition and forestall overfitting. The prepared model can then be used to arrange paddy sicknesses in new and concealed pictures, giving convenient and exact determinations that can help ranchers and horticulture specialists in pursuing informed choices with respect to illness the executives and yield wellbeing.

4.1 Algorithm

Convolutional Neural Networks (CNNs) represent a powerful deep learning approach tailored for image classification tasks. They excel at discerning intricate details, like edges, shapes, and textures, within images to facilitate precise categorization. Among these CNN architectures, ResNet-50 stands out as a highly effective option, boasting a proven track record across diverse tasks, including image classification. Comprising 50 layers, ResNet-50 is organized into four distinct blocks, each incorporating convolutional layers followed by max pooling. At the end of the network, there is a fully connected layer that makes the ultimate decision for classifying the image. The ResNet-50 architecture has consistently excelled in image classification tasks, including the important area of paddy disease classification, consistently achieving top-notch results. This approach has the potential to deliver accurate and timely disease identification, even when images exhibit variations in quality and conditions.

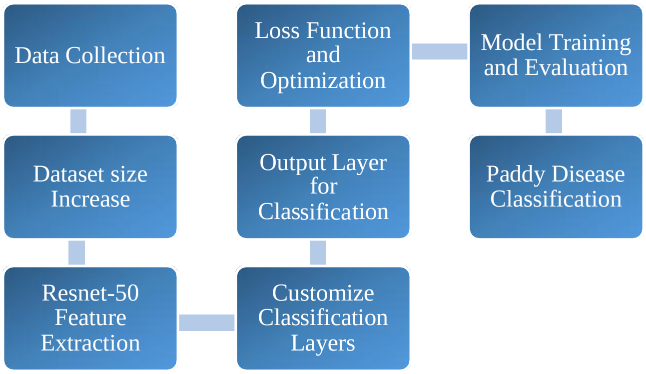

Fig. 2. Architecture of proposed system

Figure 2 displays the system's architecture and how its components work together, making it a crucial reference for understanding how the system operates.

4.2 Load Data

Stacking information is the underlying move toward any AI project. Assemble a dataset of paddy illness pictures, guaranteeing each picture is marked with the relating sickness class. Sort out your dataset into preparing, approval, and test sets, ordinarily with a split proportion like 80% preparation and 20 % test. This division helps in model preparation, approval, and assessment.

4.3 Data Pre-Processing

Resize all pictures to a predictable size (e.g., 224x224 pixels), as the ResNet-50 model anticipates a decent info size. Standardize pixel values to a standard reach (e.g., [0, 1] or [-1, 1]). This works on model combination. Apply information expansion procedures like revolution, scaling, flipping, and irregular trimming to increment dataset variety and further develop speculation.

4.4 Feature Extraction

Load the pre-prepared ResNet-50 model without its last characterization layer. Freeze the loads of the ResNet-50 layers to keep them from being refreshed during preparing. Pass the pre-handled pictures through the ResNet-50 layers and concentrate include vectors from one of the moderate layers. These component vectors address significant level conceptual elements of the pictures.

$$(I;W) = ResNet\ 50(I;W) \tag{1}$$

In Eq. (1), where I be the input image of a paddy leaf, F be the feature extraction function of ResNet-50, W be the model weights (parameters) to be learned.

4.5 Classification Using CNN with Resnet-50

Add at least one completely associated layer with suitable enactment capabilities and dropout to forestall overfitting. The last result layer ought to have however many units as there are illness classes, with a SoftMax initiation capability to create class probabilities. Accumulate the model with a proper misfortune capability, enhancer, and assessment metric.

$$Outputma[I] = Filters[I] * Activation[I-1] + Bias[I] \tag{2}$$

In Eq. (2), where $Outputma[I]$ as output future map, $Filters[I]$ as learnable convolutional filters, $Activation[I-1]$ as activation from the previous layer and $Bias[I]$ as bias term.

Table 1. Paddy Disease Classification

S.NO	IMAGE_ID	LABEL
1	10010	Normal
2	10011	Bacterial_leaf_streak
3	10012	Hispa
4	10013	Normal

The Table 1 illustrates the paddy disease classification process. It provides a visual representation of how the system categorizes different paddy diseases based on the input data.

5 Result and Discussion

In a fruitful execution, the prepared model would show high precision in grouping paddy illnesses, precisely recognizing and sorting different sickness types, for instance, the model's effectiveness will be assessed through established metrics like precision, accuracy, recall, and F1-score. The results will showcase its competency in effectively classifying various categories such as Brown Spot, Blight, Bacterial Leaf Scourge, and others. After training and validation, the model demonstrated an accuracy of 97%. The model's capacity to sum up to new and inconspicuous pictures is critical, mirroring its availability for pragmatic use. The effective execution of the proposed paddy sickness order framework utilizing a CNN with the ResNet-50 module would yield noteworthy outcomes concerning illness recognizable proof precision, power, and potential for genuine application in horticulture. These outcomes hold guarantee for essentially further developing yield the board, decreasing misfortunes, and eventually adding to worldwide food security.

Table 2. Accuracies Model Comparison

EPOCH	ACCURACY	AVERAGE LOSS
1	93.9	0.203975
2	95.7	0.151155
3	95.5	0.165245
4	97	0.110756

The completed accuracy level of 97 % in Table 2 is a good-sized milestone for the rural network, as it equips them with a powerful tool for early ailment detection and intervention, ultimately ensuing in accelerated crop yields and minimized losses.

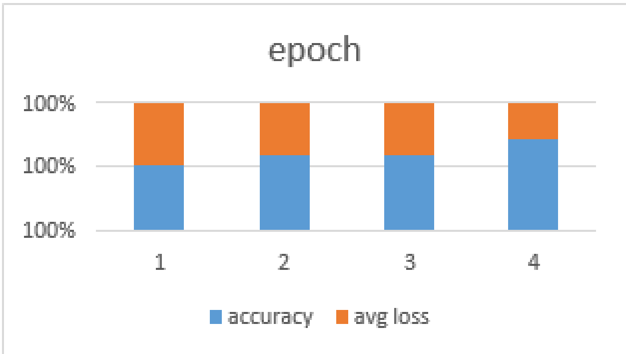

Fig. 3. Accuracy graph

The Figure 3 presents a graph showing the accuracy and lack of the ResNet-50 version. This graph visually represents how nicely the model predicts the target values and the extent of blunders in its predictions throughout both development and testing process.

6 Conclusion

All in all, the proposed paddy illness order framework, fuelled by a Convolutional Brain Organization (CNN) with the ResNet-50 design, addresses a ground breaking answer for the rural area. This framework saddles the capacities of profound getting the hang of, tending to the basic requirement for exact and opportune sickness recognizable proof in paddy crops. With a strong dataset, thorough model preparation, and cautious approval, the framework is ready to convey opportune and exact judgments, offering priceless help to ranchers and rural specialists. By supporting quick sickness, the executive's choices and advancing harvest wellbeing, this framework adds to additional maintainable and productive agrarian practices. The proposed framework not just holds guarantee in limiting harvest misfortunes and expanding yields yet in addition highlights the ground breaking influence of innovation in moulding the eventual fate of farming. As we proceed to refine and develop this framework, it is ready to assume a significant part in getting the world's food supply and supporting horticultural manageability.

7 Future Enhancement

To enhance the dataset, the team need to gather a wider variety of paddy disease images, making the model more effective at identifying a broader range of diseases. The team can also include geographical and environmental data to understand disease patterns and their connections to specific locations and conditions. Improving the model's architecture is promising; experimenting with different CNN structures or advanced techniques like attention mechanisms may enhance classification performance. Real-time disease monitoring and automated intervention systems can greatly benefit agriculture. By integrating the model into a user-friendly smartphone or robot application for in-field disease detection, farmers can take timely action. Scalability and adaptability are essential, so the team should design a robust system that can accommodate new disease categories and apply to various crops.

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