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Predicting the Rice Leaf Diseases Using CNN

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Abstract: In India, rice is a crucial crop, yet it faces significant threats from various diseases throughout its growth cycle. Identifying these diseases manually is challenging, especially for farmers with limited expertise. Leveraging advancements in deep learning research, automated picture identification systems based on Convolutional Neural Network (CNN) models offer a promising solution. This study presents a CNN model for disease identification in rice plants, developed through Transfer Learning on a small dataset due to limited availability of rice leaf disease images. Specifically, the VGG-16 architecture is employed for training and evaluation purposes. The model utilizes a combination of rice field and internet datasets, demonstrating its adaptability to real-world scenarios. Despite the challenges posed by the scarcity of labeled data, the proposed CNN architecture achieves a commendable accuracy rate of 95 percent in disease classification. The utilization of Transfer Learning allows for efficient knowledge transfer from pre-trained models, enhancing the model's performance even with limited training samples. This research contributes to the field of agricultural technology by offering a reliable and accessible tool for disease identification in rice plants. By empowering farmers with automated systems capable of accurate disease diagnosis, this work aims to mitigate crop losses and improve agricultural productivity, ultimately benefiting food security and livelihoods in rice-growing regions.

Index Terms: Rice Leaf Diseases, Prediction, Convoloutional Neural Networks, Plant Disease Detection, Crop Diseases

1. INTRODUCTION

Rice stands as a cornerstone of global nutrition, particularly in countries like India, where it serves as a primary dietary staple for millions [1]. However, the journey of rice from seedling to harvest is fraught with challenges posed by various diseases that threaten crop yield and food security. Prompt and accurate diagnosis of these diseases is imperative for effective treatment and maintaining high-quality yields. Yet, the vast expanses of agricultural land, the multitude of diseases afflicting rice plants, and the scarcity of agricultural expertise in remote areas present formidable obstacles to timely diagnosis and intervention [2].

Traditional methods of disease identification rely heavily on human expertise, necessitating the presence of agricultural specialists, which can be scarce and time-consuming to access in remote regions. Moreover, the diverse array of diseases that can afflict rice plants, often co-occurring within a single crop, further complicates manual diagnosis [3]. To address these challenges and empower farmers with timely disease detection and management tools, automated systems utilizing artificial intelligence (AI) techniques have garnered attention in recent years [4].

Artificial neural networks (ANNs) and support vector machines (SVMs) have been explored in previous studies for disease identification in plants. However, the efficacy of these systems is heavily reliant on the selection of discriminative features, which can be subjective and labor-intensive [5]. The advent of convolutional neural networks (CNNs) has revolutionized the field of image recognition by enabling automatic feature extraction directly from raw image data, obviating the need for manual feature engineering [6].

One significant challenge in developing AI-based systems for disease identification in agriculture is the availability of large, labeled datasets for model training. Acquiring such datasets, particularly for specific crops and diseases, can be arduous and expensive. To circumvent this challenge, Transfer Learning has emerged as a powerful technique, allowing researchers to leverage pre-trained models on large datasets and adapt them to new tasks with smaller datasets [7].

In this paper, we propose a novel approach for automated disease classification in rice plants, leveraging deep learning techniques, specifically CNNs, and Transfer Learning. The proposed system aims to address the limitations of traditional disease identification methods by providing farmers with a user-friendly tool accessible through their smartphones [8].

By capturing images of diseased rice leaves using their smartphones and submitting them to a central server, farmers can receive rapid and accurate diagnoses, along with recommended treatment strategies, facilitating timely intervention and minimizing crop losses [9]. This concept harnesses the ubiquity of mobile technology to democratize access to agricultural expertise and empower farmers with actionable insights [10].

Central to our approach is the utilization of Transfer Learning to fine-tune a pre-trained VGG-16 model, a widely adopted CNN architecture, to classify rice leaf diseases accurately. By adapting the model's fully connected layers to the specific characteristics of our dataset, we aim to enhance its performance in disease identification tasks [11].

Throughout the development of our automated disease classification system, we conducted rigorous analysis to identify and rectify any shortcomings. By examining instances of misclassification and understanding the underlying causes, we iteratively refined our model to improve its accuracy and robustness [12].

In summary, this paper presents a comprehensive overview of our approach to automated disease classification in rice plants, leveraging deep learning techniques and Transfer Learning. Through the integration of AI-based systems with mobile technology, we aim to democratize access to agricultural expertise and empower farmers with the tools they need to safeguard their crops and livelihoods [13].

2. LITERATURE SURVEY

Plant diseases pose significant threats to agricultural productivity and food security worldwide. Traditional methods of disease identification and management often rely on human expertise, which can be limited and time-consuming, particularly in remote agricultural regions. In recent years, researchers have increasingly turned to artificial intelligence (AI) techniques, including machine learning algorithms and deep learning models, to develop automated systems for disease detection and classification in plants. This literature survey provides an overview of existing studies focusing on disease analysis in plants, with a particular emphasis on image-based approaches utilizing Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), and Transfer Learning.

SVMs have been widely employed in various domains, including plant disease analysis. Gupta et al. [9] proposed a modified SVM-CS classifier for plant leaf disease analysis using image processing techniques. Their study demonstrated the effectiveness of SVMs in distinguishing between different types of plant diseases based on leaf images. Similarly, Es-saady et al. [10] presented an automatic recognition system for plant leaf diseases, utilizing a serial combination of two SVM classifiers. Their approach achieved promising results in accurately identifying and classifying plant diseases based on image features.

Padol and Yadav [12] focused on grape leaf disease detection using an SVM classifier. Their study highlighted the applicability of SVMs in detecting and diagnosing diseases affecting grape leaves, contributing to the advancement of precision agriculture practices. These studies underscore the utility of SVMs in plant disease analysis and emphasize the importance of feature selection and classification techniques in achieving accurate disease identification.

In recent years, CNNs have emerged as powerful tools for image recognition and classification tasks, including plant disease analysis. Liu and Zhou [13] utilized a Backpropagation (BP) neural network for the extraction of rice leaf disease images, demonstrating the potential of neural networks in identifying plant diseases based on visual cues. Arivazhagan and Ligi [14] employed a CNN for mango leaf diseases identification, achieving high accuracy in classifying different types of mango leaf diseases from images.

Furthermore, Liu et al. [17] developed a hybrid CNN-SVM classifier for identifying apple leaf diseases, leveraging the complementary strengths of CNNs and SVMs. Their approach demonstrated superior performance in recognizing handwritten digits, showcasing the efficacy of combining deep learning and traditional machine learning techniques for disease classification tasks. Lu et al. [20] focused on rice disease identification using deep CNNs, achieving notable success in accurately detecting and classifying rice diseases based on leaf images.

Transfer Learning has emerged as a valuable technique for addressing the challenge of limited labeled data in plant disease analysis. Atole and Park [22] proposed a multiclass deep CNN classifier for detecting common rice plant anomalies. Their study highlighted the effectiveness of Transfer Learning in adapting pre-trained CNN models to new disease classification tasks, facilitating accurate identification of rice plant anomalies.

These studies collectively demonstrate the growing interest in utilizing AI-based approaches, including SVMs, CNNs, and Transfer Learning, for plant disease analysis. By leveraging advanced machine learning and deep learning techniques, researchers aim to develop automated systems capable of accurately identifying and classifying plant diseases, thereby enhancing agricultural productivity and ensuring global food security. However, further research is needed to address challenges such as dataset availability, model generalization, and real-world deployment of automated disease detection systems.

Overall, this literature survey provides insights into the current state of research in plant disease analysis and highlights the potential of AI techniques in revolutionizing agricultural practices. By integrating AI-driven solutions with traditional agricultural methods, researchers seek to empower farmers with tools for early disease detection and proactive management, ultimately contributing to sustainable agriculture and food production [22].

3. METHODOLOGY

a) Proposed Work:

In this proposed work, a VGG16 transfer learning neural network is utilized to address the challenge of training a dataset of rice diseases for accurate prediction from new photos. The author encountered limitations with the Rice Leaf dataset from KAGGLE due to its small size, prompting the adoption of transfer learning CNN algorithms. Transfer learning involves transferring knowledge from an existing CNN [7] model to a new dataset and then fine-tuning the model using the new data. By leveraging the pre-trained VGG16 model, which has been trained on a large dataset, the proposed approach aims to enhance prediction accuracy for rice disease identification. Comparative analysis will be conducted to evaluate the performance of the VGG16 [9] transfer learning model against both a normal CNN model and a normal CNN model with VGG16 transfer learning. Through this research, insights into the efficacy of transfer learning in improving prediction accuracy for rice disease identification will be gained, potentially offering valuable advancements in agricultural technology and crop management strategies.

b) System Architecture:

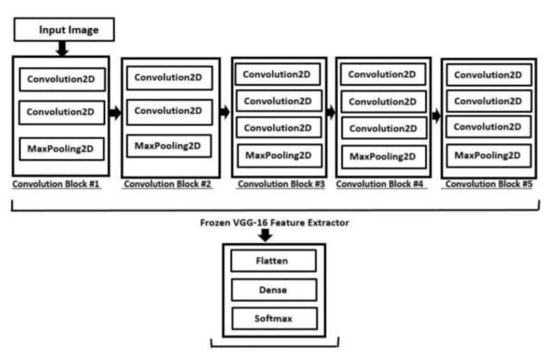


Fig1 Proposed Architecture

The proposed system architecture utilizes the VGG16 Convolutional Neural Network (CNN) [7] design, renowned for its effectiveness in vision tasks. The VGG16 architecture comprises multiple layers of 3x3 convolution filters with a stride of 1, accompanied by 2x2 max-pooling layers with a stride of 2 and padding. This consistent arrangement of convolution and max-pool layers throughout the architecture is a key characteristic of VGG16. The network consists of 16 weighted layers, denoted by the name "VGG16," and includes two fully connected (FC) layers followed by a softmax output layer. With approximately 138 million parameters, VGG16 offers substantial capacity for learning intricate patterns in image data. Leveraging this architecture, the system aims to accurately classify rice diseases from input images, leveraging the extensive representational power of VGG16 [9] for effective feature extraction and disease identification.

c) Experimental Setup:

For the experimental setup, a 64-bit Windows 10 PC was employed. The Convolutional Neural Network (CNN) model was constructed using Keras 2.2.4 deep learning framework, with TensorFlow 1.14.0 serving as the backend. Python 3.7.2 was utilized for coding and implementation. This setup ensured compatibility and stability, facilitating the development and execution of the CNN model for the intended experiments.

d) Processing of images:

Images for the dataset were sourced both from field captures and online sources, encompassing various rice diseases and healthy plant samples. Image processing involved enhancement techniques such as zoom, rotation, and horizontal/vertical shifts applied using Keras' ImageDataGenerator. This preprocessing step augmented the dataset by generating new images at a resolution of 224x224 pixels. These enhanced images contributed to a more diverse and robust dataset for training the Convolutional Neural Network (CNN) [7] model.

e) CNN Modeling School:

In the CNN's modeling process, the picture dataset is loaded, and class labels and images are stored separately for training purposes. A 70-30 train-test split is applied, with 30% of the data allocated for validation. Class labels are encoded using one-hot encoding, and the final fully connected layers are removed from Keras. Untrainable additions are made to the system, followed by the application of a softmax filter to the feature extractor's flattened output. The model is trained using the Adam optimizer and categorical crossentropy loss function. Training halts after 25 epochs, ensuring stable results. Figure 3 illustrates the classification procedure steps undertaken.

f) Algorithms:

CNN:

Convolutional Neural Network is utilized for image classification tasks, such as identifying diseases in rice plants. This algorithm is specifically designed to analyze visual data by employing convolutional layers to extract features from images. By leveraging its hierarchical structure, CNNs [7] can automatically learn relevant features and patterns, enabling accurate classification of images. In the context of rice disease detection, CNNs are employed to analyze leaf images and classify them into different disease categories, aiding farmers in early disease diagnosis and effective crop management strategies.

ResNet-101

ResNet-101 is a convolutional neural network architecture that has various layers.

The ResNet architecture is usually divided into four parts, each containing multiple residual blocks .

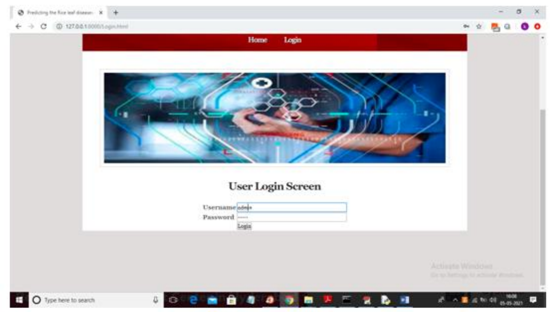
The first part of the Network comprises a single convolutional layer, followed by max pooling, to reduce the spatial dimensions of the input.

The second part of the Network contains 64 filters, while the third and fourth parts contain 128 and 256 filters, respectively. The final part of the Network consists of global average pooling and a fully connected layer that produces the output .

ResNet-101 is a deep residual network that is designed to address the vanishing gradient problem in deep neural networks. It is composed of multiple residual blocks, each of which contains skip connections that allow the network to learn residual mappings.

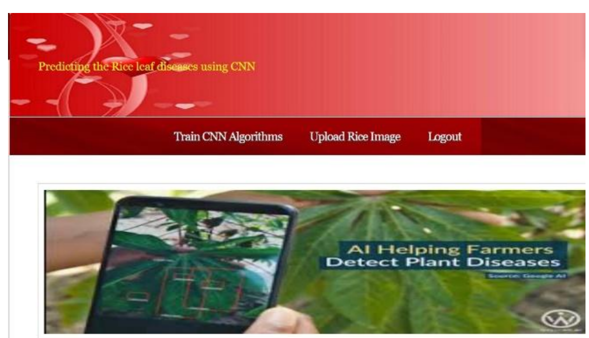
4. EXPERIMENTAL RESULTS

Open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below screen

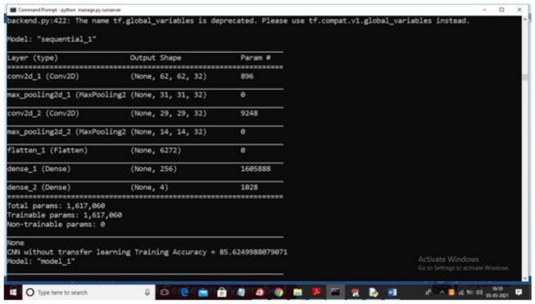


In above screen enter username as 'admin' and password as 'admin' and then click on 'Login' button to get below screen

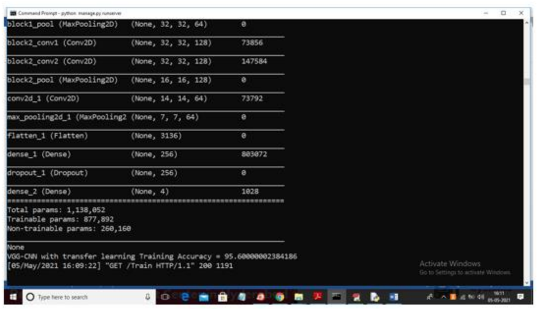
In above screen click on 'Train CNN Algorithms' link to train both VGG16 and normal CNN without transfer learning on rice dataset and then calculate prediction accuracy



Algorithm Name	Test Accuracy
CNN with Transfer Learning	95.60000002384186
CNN without Transfer Learning	85.6249988079071
Extension Resnet101	96.875

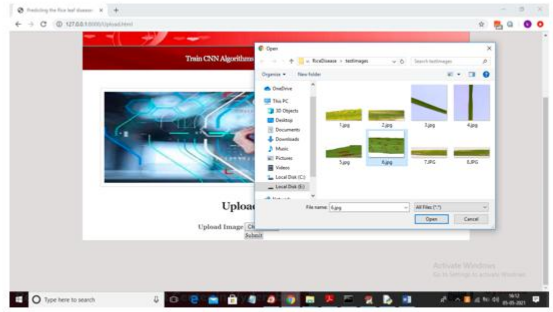


In above screen normal CNN created 4 layers and got 85% accuracy and in below screen you can see VGG16 layers



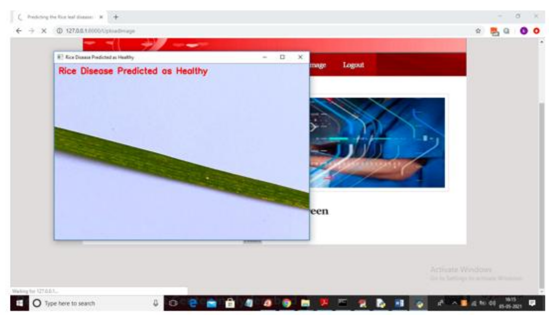
In above screen VGG16 contains so many layers and its accuracy is 95% and now in below screen click on 'Upload Rice Image' link

Now in above screen click on 'Choose File' button to upload leaf test image from 'testImages' folder



In above screen selecting and uploading '6.jpg' file and then click on 'Open' button then click on 'Submit' button to get below result

In above screen in uploaded image disease predicted as 'Leaf Blast' and now test other image



In above screen leaf predicted as healthy and similarly you can upload other images and test them

5. CONCLUSION

In this research, we present a deep learning architecture, specifically a Convolutional Neural Network (CNN), designed to classify rice leaf diseases with accuracy rate of 95% on a test dataset

to increase model performance we used Resnet-101 algorithm and accuracy is increased to 96% the CNN's performance was significantly enhanced through fine-tuning of the VGG16 model. By

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adapting the pre-trained VGG16 [9] architecture to our specific dataset, we harnessed its powerful feature extraction capabilities, enabling precise classification of rice leaf diseases.

The to prevent overfitting.

Our research highlights the transformative potential of deep learning techniques, such as CNNs [7], in revolutionizing agricultural practices. By providing farmers with tools for early disease detection and precise management strategies, we can mitigate crop losses and enhance food security in rice-growing regions. Future endeavors could focus on scaling up the application of CNN-based disease classification models in real-world agricultural settings, facilitating widespread adoption and sustainable crop management practices.

6. FUTURE SCOPE

In future research, expanding the dataset with additional photos sourced from agricultural areas and research organizations will be crucial to further enhance the accuracy of our results. Introducing a cross-validation mechanism will provide additional validation of our findings, ensuring robustness and reliability. Furthermore, comparing our model's performance with more advanced deep learning architectures and ongoing efforts in the field will offer valuable insights into its efficacy and potential areas for improvement. Additionally, extending the scope of our model to detect other plant leaf diseases, particularly those affecting significant crops in India, holds promise for addressing broader agricultural challenges. By continually refining and validating our approach, we can advance the application of deep learning techniques in agricultural settings, ultimately contributing to improved crop management practices and food security.

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