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IMPROVING RICE CROP YIELD USING DEEP LEARNING BASED SMART DESIESE DETECTION PLATFORM

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Abstract: The rice leaf suffers from several bacterial, viral, or fungal diseases and these diseases reduce rice production significantly. Hence early detection of the rice leaf diseases is very important. To sustain rice demand for a vast population globally, the recognition of rice leaf diseases is crucially needed. However, recognition of rice leaf disease is limited to the image backgrounds and image capture conditions. This project proposes a solution for the automated classification of rice leaf diseases using the ResNet-50 architecture. Rice is a vital crop, but it is susceptible to various diseases that can cause significant yield losses. The traditional method of manually identifying and classifying rice leaf diseases is time-consuming and often requires experienced professionals. Therefore, there is a need for an automated solution to classify rice leaf diseases accurately and efficiently. In this paper, we collect a dataset of rice leaf images, preprocess it, train the ResNet-50 model, and evaluate its performance.

Index Terms **– Leaf Disease, Resnet50, crop yield, CNN.**

I. INTRODUCTION

Rice is the world's most important food crop and furnish food for more than half of the population. In the last 20 years, 3 lakhs farmers have committed suicides, due to yield loss. Farmers lose an estimated average of 37% of their rice crop due to pests and diseases every year. So, identifying, analyzing, predicting the disease must be fast to upgrade production. The diseases are mostly caused by Bacteria, Fungus, Virus and others like mosquito, green hoppers etc. Mostly occurred bacteria diseases are Bacterial Leaf Blast, foot rot etc. and fungus are brown spot, narrow brown spot, etc. are more occurred virus disease. ResNet-50 algorithm plays a key role to improve the accuracy for detecting diseases. The goal of this project is to develop a Disease Prediction for rice fields.The system provides a platform where users can identifythe rice leaf disease by just providing the leaf pictures as input and hence related cure can be done.

The objective of this project is to predict the type of the disease of a rice leaf. So appropriate pesticides or fertilizers can be used based on the type of thedisease to get a good yield.

II. LITERATURE SURVEY

Specific algorithms based on artificial intelligence and neural networks are also being proposed and implemented to predict the rice leaf diseases with increased accuracy. The distribution of the datasets used for disease detection is highly with low accuracy. So, to overcome this obstacle, under- sampling and oversampling techniques are being designed to obtain comparatively balanced data. ResNet-50 one of the Convolutional Neural Network architecture are also being implemented in order to create a more efficient Rice Leaf Disease Detection System. Another important area of development is the emergence of new hybrid models. These are derived from preexisting supervised as well unsupervised deep learning techniques. Hybrid Models may be able to produce a more accurate result as theyenraptured the capabilities of both supervised as well as unsupervised deep learning.

[1] Extraction of the Rice Leaf Disease Image based on BP Neutral Network

Rice leaf diseases have occurred all over the world, including China. They have had a significant impact on rice quality and yield. Now, the control method relies mainly on artificial means. In this study, BP neural network classifiers were designed for classifying the healthy and diseased parts of rice leaves. This paper selects rice brown spot as study object, the training and testing samples of the images are gathered from the northern part of Ningxia Hui Autonomous Region. The result shows that the scheme is feasible to identify rice brown spot using image analysis and BP neural network classifier.

[2] Identification of Apple Leaf Diseases Based on Deep Convolutional Neutral Networks Symmetry

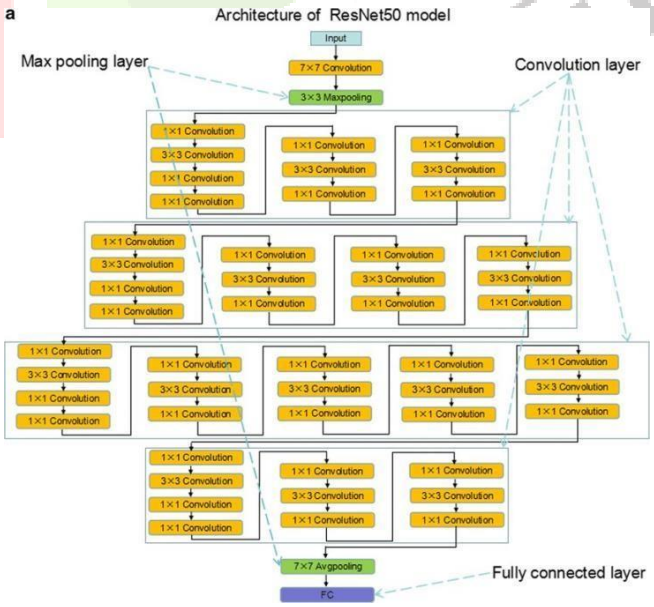
Mosaic, Rust, Brown spot, and Alternaria leaf spot are the four common types of apple leaf diseases. Early diagnosis and accurate identification of apple leaf diseases can control the spread of infection and ensure the healthy development of the apple industry. The existing research uses complex image pre-processing and cannot guarantee high recognition rates for apple leaf diseases. This paper proposes an accurate identifying approach for apple leaf diseases based on deep convolutional neural networks. It includes generating sufficient pathological images and designing a novel architecture of a deep convolutional neural network based on AlexNet to detect apple leaf diseases. Using a dataset of 13,689 images of diseased apple leaves, the proposed deep convolutional neural network model is trained to identify the four common apple leaf diseases. Under the hold-out test set, the experimental results show that the proposed disease identification approach based on the convolutional neural network achieves an overall accuracy of 97.62%, the model parameters are reduced by 51,206,928 compared with those in the standard AlexNet model, and the accuracy of the proposed model with generated pathological images obtains an improvement of 10.83%. This research indicates that the proposed deep learning model provides a better solution in disease control for apple leaf diseases with high accuracy and a faster convergence rate, and that the image generation technique proposed in this paper can enhance the robustness of the convolutional neural network model.

[3] Hyper Class Augmented and Regularized Deep Learning for Fine-Grained Image Classification

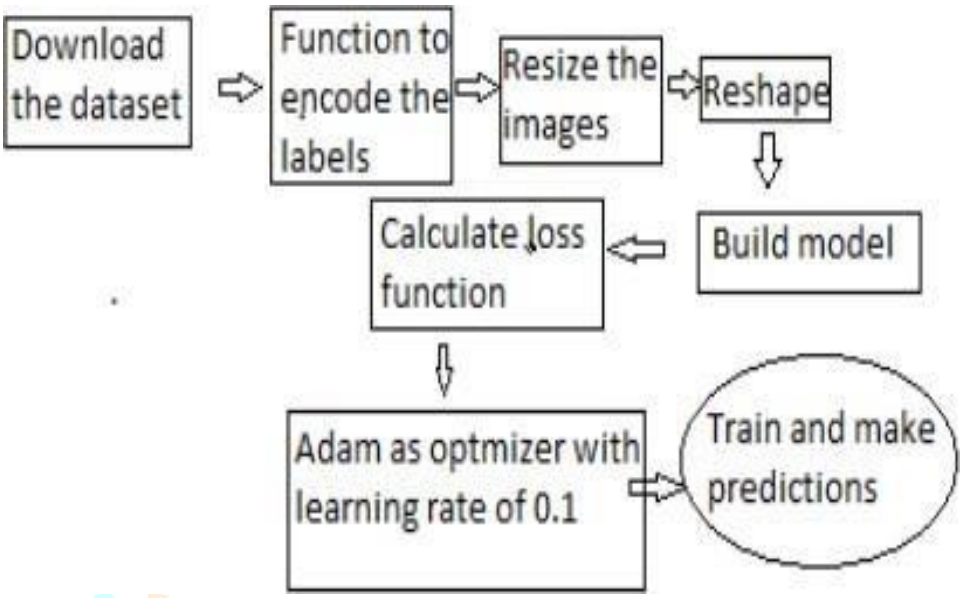
Deep convolutional neural networks (CNN) have seen tremendous success in large-scale generic object recognition. In comparison with generic object recognition, fine-grained image classification (FGIC) is much more challenging because (i) fine-grained labeled data is much more expensive to acquire (usually requiring domain expertise); (ii) there exists large intra-class and small inter-class variance. Most recent work exploiting deep CNN for image recognition with small training data adopts a simple strategy: pre-train a deep CNN on a large-scale external dataset (e.g., ImageNet) and fine-tune on the small-scale target data to fit the specific classification task. In this paper, beyond the fine-tuning strategy, we propose a systematic framework of learning a deep CNN that addresses the challenges from two new perspectives: (i) identifying easily annotated hyper- classes inherent in the fine-grained data and acquiring a large number of hyper- class-labelled images from readily available external sources (e.g., image search.

III. METHODOLOGY

The ResNet-50 architecture consists of 50 layers, including convolutional, pooling, and fully connected layers. It has skip connections that allow the network to learn residual functions instead of directly fitting a desired mapping. This architecture solves the problem of the vanishing gradient during back propagation in very deep neural networks.
Overall, the ResNet-50 architecture achieves state-of-the-art performance on various image classification benchmarks and is widely used in many computer vision applications..



The above mention fig is about the workflow of the system.

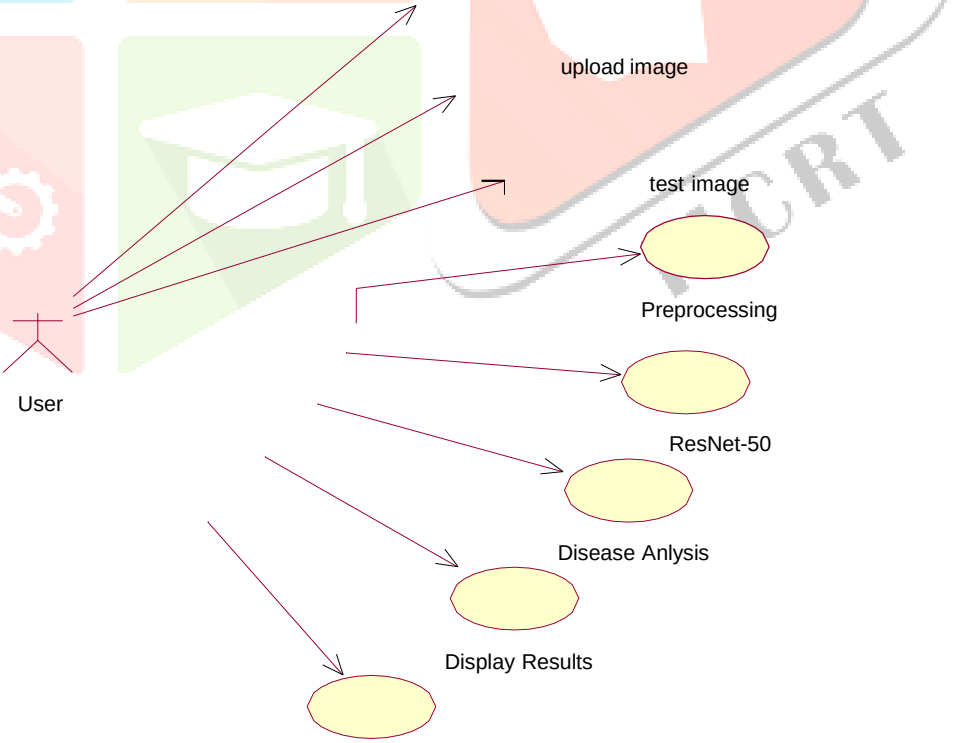


The work flow of the system is discussed as follows:

A. Login: This is an online application and user need to login by using username as 'admin' and password as 'admin'

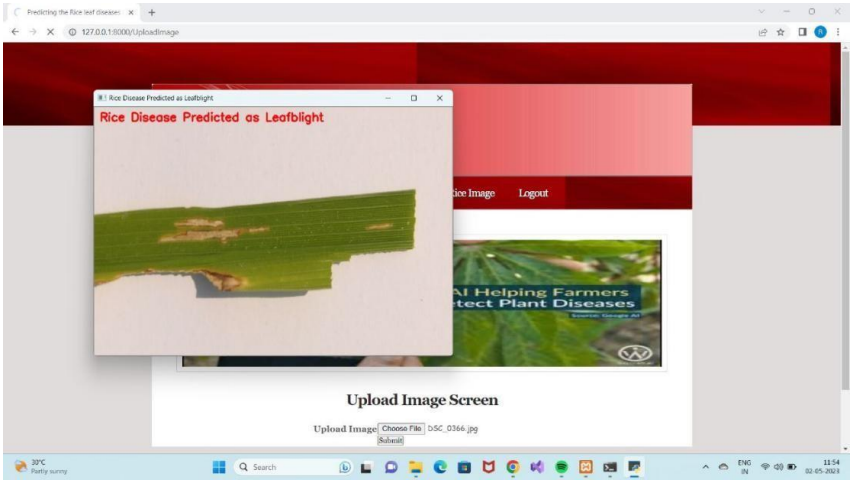
B. Train ResNet-50 Algorithms: After login user can use this model to train ResNet-50 with above rice disease dataset and after training model we will calculate both models accuracy on test data.

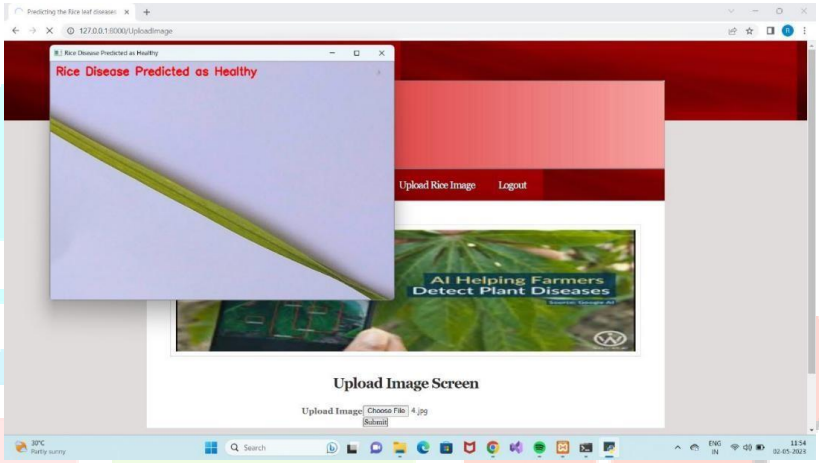
C. Upload Rice Image: using this module we will allow user to upload rice leaf



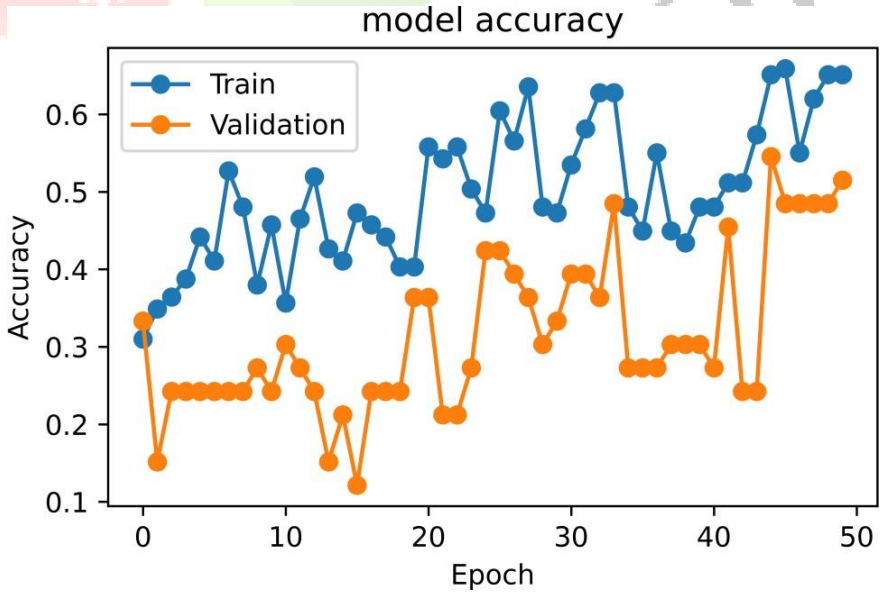
IV. RESULTS AND DISCUSSION

The screenshots of the system are shown below.





The resnet50 model accuracy with various epochs is as shown in the figure below.



V. CONCLUSION

In this project, we used ResNet-50 one type of Convolutional Neural Network (CNN) architecture to train rice diseases dataset and after training we can use this model to predict disease from new images. In conclusion, using Resnet-50 for rice leaf disease classification can be an effective approach for identifying and categorizing diseases affecting rice crops. By training a Resnet-50 model on a labeled dataset of rice leaf images, the model can learn to differentiate between healthy and diseased leaves and classify the specific disease present in the image.Fine-tuning a pre-trained Resnet-50 model or training a Resnet-50 model from scratch can both be effective approaches, depending on the availability of data and computational resources. Transfer learning with a pre-trained model can save time and resources, while trainingfrom scratch can potentially lead to higher accuracy

After the continues trials and training of the system, we have succeeded to detectand predict the two major rice leaf diseases such as Brown Spot, Leaf blight ,Leaf Blast and healthy leaf with 81.8% of accuracy by using ResNet-50. But there is a scope to acquire 100% of accuracy by using the upcoming and latest technologies developed with Deep Learning, Machine Learning and Image Processing. We hope for the best and 100% of accuracy to detect the exact rice leaf diseases and it would be better to predict and detect the more types rice leaf diseases to help the farmers and to increase the rice crop yield.

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