Detection of Rice Leaf Disease using Machine learning Techniques

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Introduction

1. Rice is a critical crop and primary food source for many in the Indian subcontinent.
2. Rice leaf diseases can cause significant yield losses, lower grain quality, and crop failure.
3. Prompt diagnosis and treatment of rice leaf diseases are vital for sustainable agriculture and food security.
4. Convolutional neural networks (CNNs) have the ability to automate the identification of plant diseases.
5. A CNN-based model is suggested for identifying rice leaf diseases using digital photographs of leaves.
6. The model is trained using a large dataset of labeled rice leaf images affected with various diseases.
7. The model uses fully connected layers to categorize leaves into illness groups and convolutional layers to extract characteristics from input photos.
8. Using digital photographs for disease detection has several benefits, including non-invasive method and early detection of diseases to minimize yield losses.

Literature Survey

1. Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., and Traore, D. (2019). In Deep neural networks with transfer learning in millet crop images demonstrated that transfer learning in CNN can be used in plant disease identification. The classification accuracy has been 95% on pre trained based on feature extraction. [4]
2. Rangarajan et al. was used two pre-trained deep learning models, AlexNet and VGG16 to classifying 6 different diseases and a healthy class of the tomato crop from the image dataset. The classification accuracy has been 99.24% for VGG16 and 96.51% for AlexNet. [5]

Literature Survey

3. Amara et al. propose a deep learning-based approach that automates the process of classifying banana leaf diseases. The authors use LeNet architecture as a deep convolutional neural network to classify banana sigatoka and speckle. They obtain 98.61% of accuracy with color images and 94.44% for gray images.[7]
4. Y. Lu, S. Yi, N. Zeng, Y. Liu, Y. Zhang in Identification of rice diseases using deep convolutional neural networks have have identified rice diseases using CNN. The study has categorized 10 classes of rice diseases on 500 images of infected rice and stems. The experience has shown that the CNN gives a better result than to traditional techniques of identifying diseases on rice, by using pattern recognition bases and machine learning. [6]
5. By monitoring electrolyte leakage, investigating the membrane's integrity, examining the cell cycle with trypan blue staining, and assessing the depth of callose deposition with aniline blue staining, biotic stress is traditionally measured in plants

Literature Survey

6. These techniques, however lab-based and ideally suited for examining the various factors that contribute to biotic stress, may not be practical or available to farmers. Apart from techniques like hyperspectral imaging, multispectral imaging, fluorescence spectrography, and sensor combinations, thermography is employed for the detection of both abiotic and biotic stressors when non-laboratory based or contemporary sensing systems are taken into account.
7. However, it is challenging to use lab-based techniques or other imaging systems at the edge. As a result, some research to address the implementation issues in networked node based agricultural vegetation monitoring have also been conducted

Problem statement

The problem statements of the project is “Detection of Rice Leaf Disease using Machine learning Techniques”

The main focus of doing this project is to provide a high accuracy model to predict the rice leaf disease and help farmers in early detecting the rice leaf disease and increase the crop yield. This is implemented in an android application which can be used by farmers even with access to slow internet connection.

Dataset

The data set used contains 5932 number images includes four kinds of Rice leaf diseases i.e. Bacterial blight, Blast, Brown Spot and Tungro.

Later the dataset was divided into 80:20 ratio for train and test dataset

Citation: Sethy, P. K., Barpanda, N. K., Rath, A. K., & Behera, S. K. (2020). Deep feature based rice leaf disease identification using support vector machine. Computers and Electronics in Agriculture, 175, 105527. doi:10.1016/j.compag.2020.105527.

Methodology

1. The project proposed a deep learning-based approach using Convolutional Neural Networks (CNNs) for detecting rice leaf diseases based on images of rice leaves.
2. CNNs are well-suited for image classification tasks and can automatically extract relevant features from input images to identify patterns and classify images with high accuracy.
3. CNNs use convolutional layers to scan and analyze the input image in a hierarchical manner and recognize particular elements at different degrees of abstraction.
4. By using CNNs to detect rice leaf disease, an automated and efficient method for disease identification and management can be developed, which can ultimately benefit farmers and improve crop yields.
5. Three models were proposed in the project, with the final model using an optimizer, data augmentation, six layers, and one hidden layer.
6. The final model achieved high accuracy in detecting rice leaf diseases and can be used as a reliable and efficient tool for disease detection and management.

Methodology

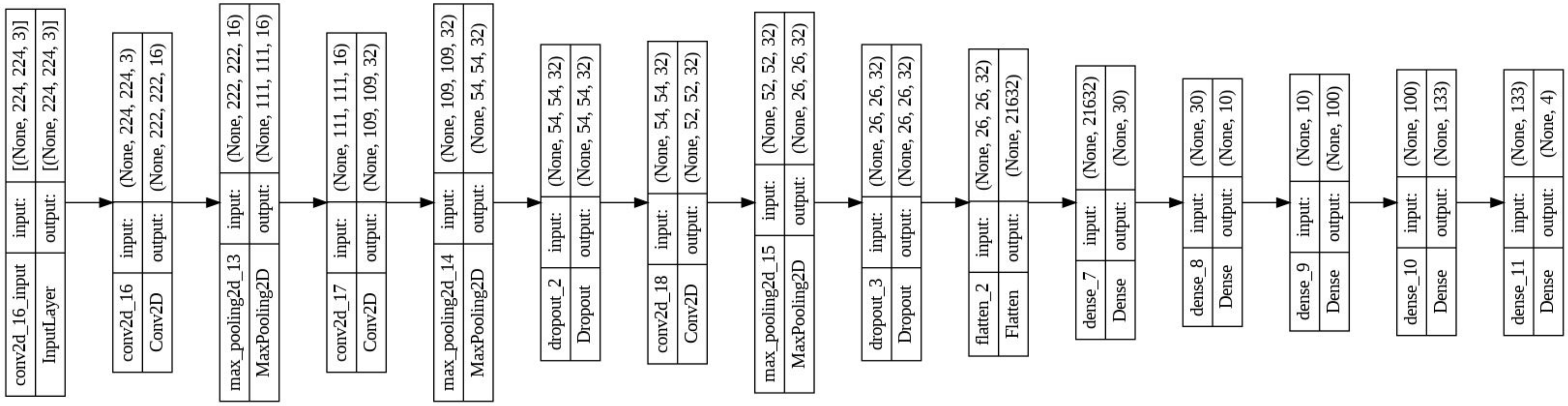


Fig. Summary of primary three layer model.

Methodology

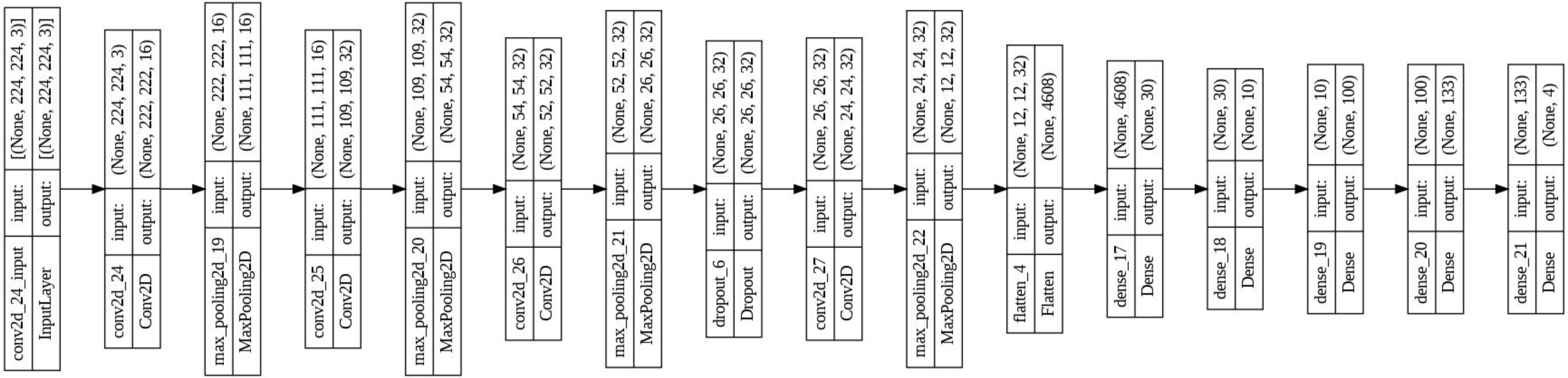


Fig. Summary of primary three layer model with added another layer of same dimension and dropout

Methodology

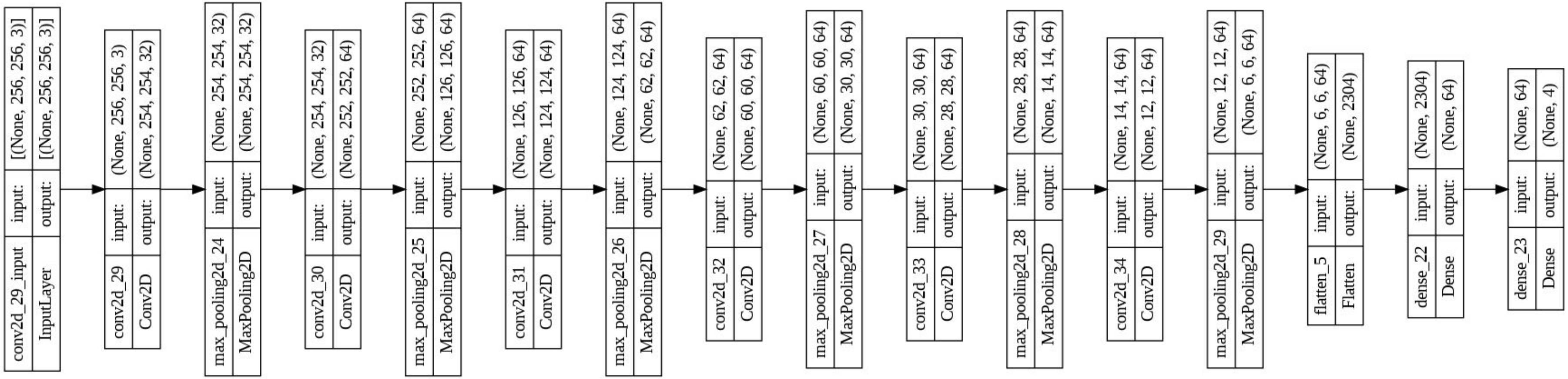


Fig. Summary of primary six layer model with added another layer of same dimension and dropout

Result

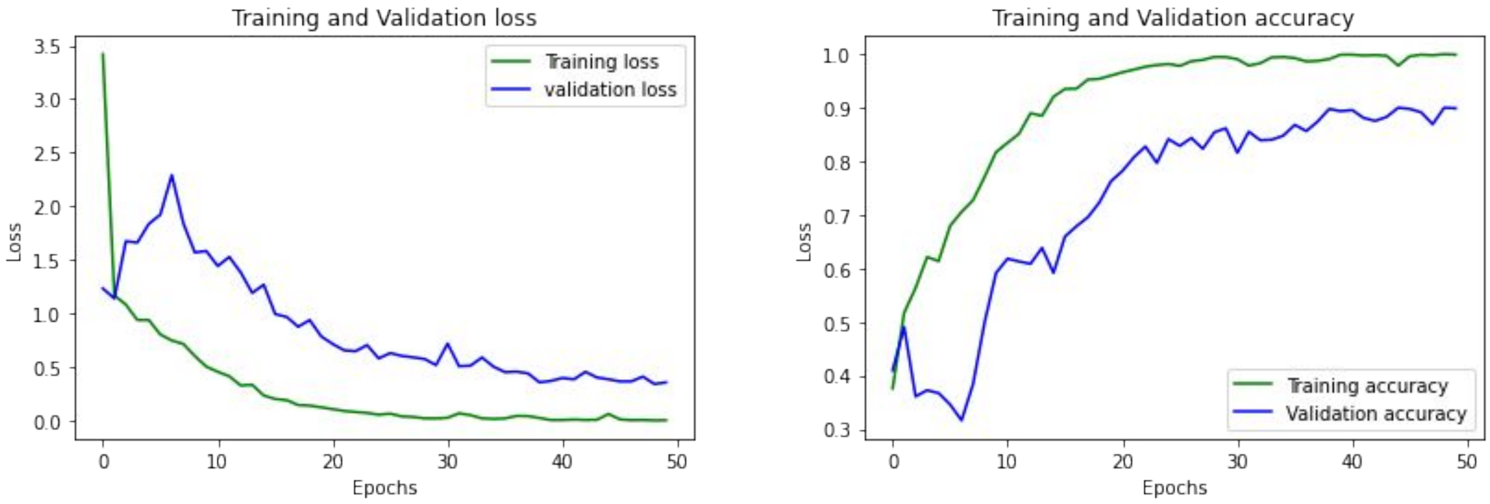
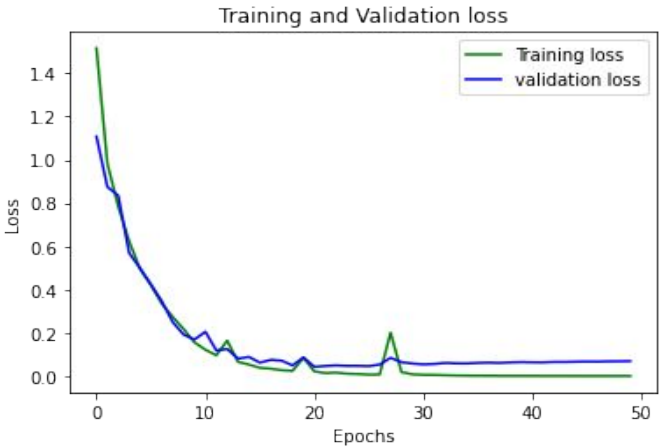


Fig. Graph of Loss vs Epoch and Accuracy vs Epoch on training and validation data of primary three layer model.

Result



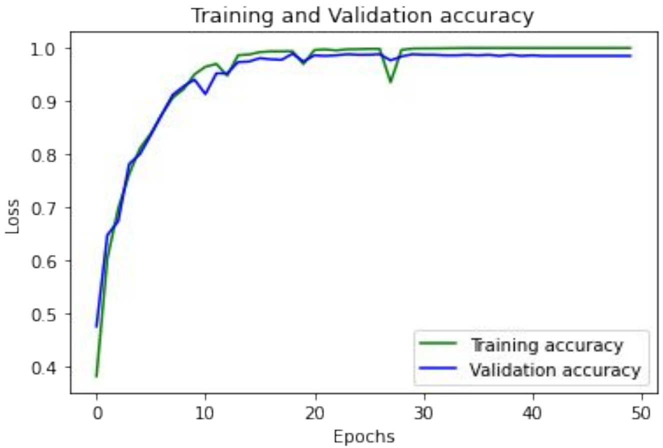
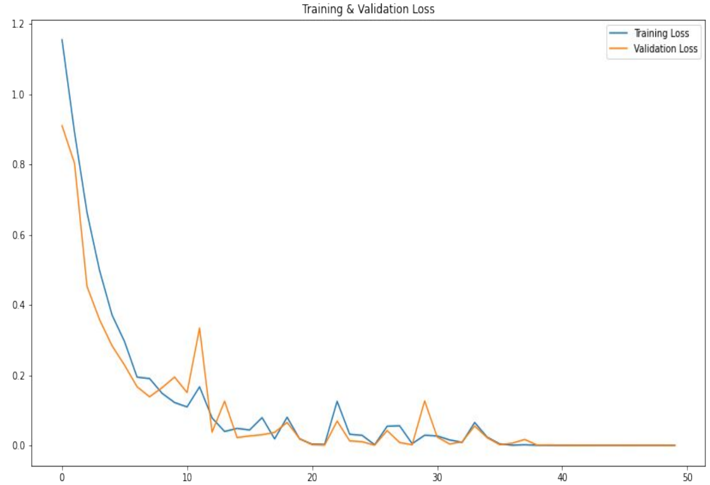


Fig. Graph of Loss vs Epoch and Accuracy vs Epoch on training and validation data of primary three layer model with added another layer of same dimension and dropout

Result



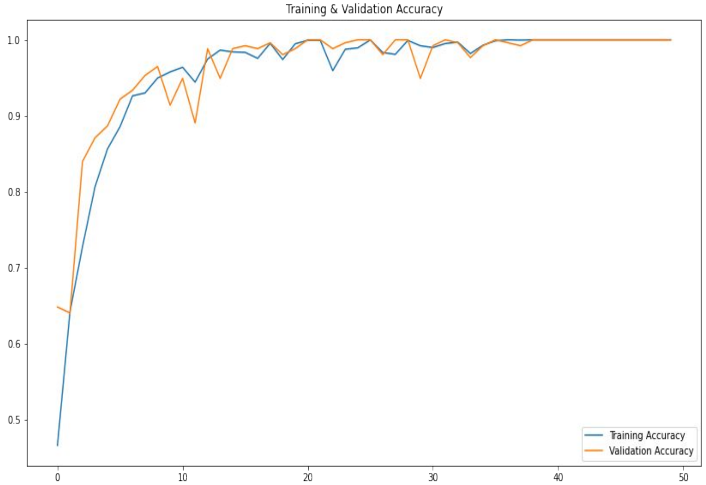


Fig. Graph of Loss vs Epoch and Accuracy vs Epoch on training and validation data of primary three layer model with added another layer of same dimension and dropout

Result

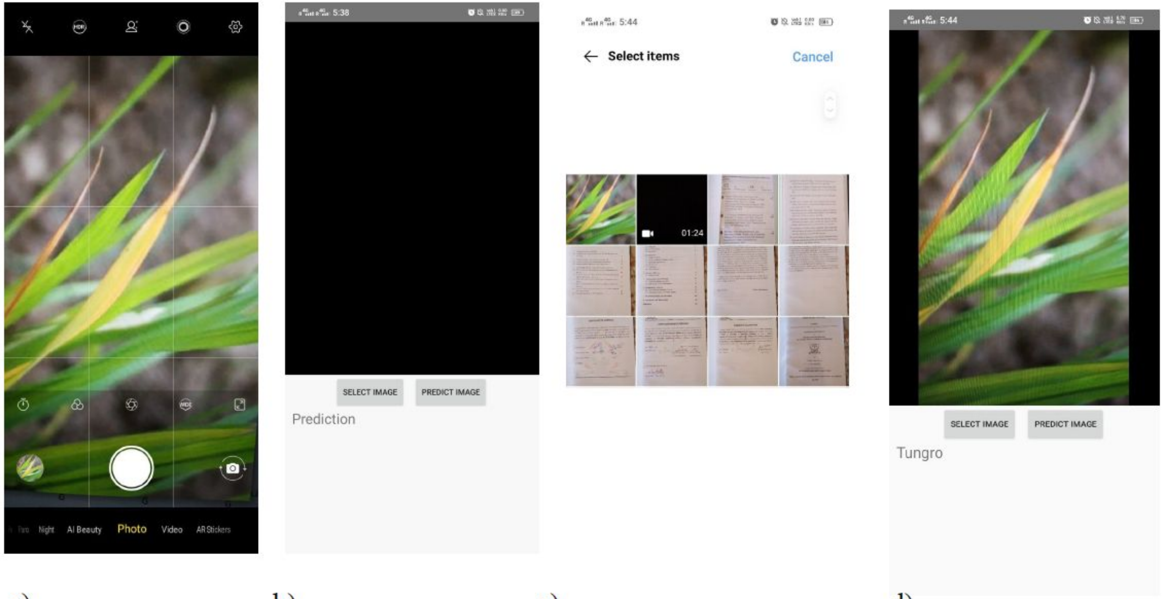
However on comparison of our model with performance of SE-ResNet-50, DenseNet-121, and ResNeSt-50 had almost the same result as that of our model validating our model performance. [1]

Deployment of model in Android App

- The model is deployed in an android model
- The application doesn’t require high speed internet connection and works offline so that the application can be used with places having slow internet connection.
- The application is easy to use

Android Application

Following is the workflow of using the android application where our project is deployed in the phone



a) b) c) d)

Fig.7 Capture image using smartphone camera (b) app launched from homescreen, (c) select image from gallery(d) the result is shown

Conclusion

- A deep learning-based approach using CNNs was proposed for the detection of rice leaf diseases.
- A model was developed and trained on a large dataset of labeled rice leaf images with an accuracy of 96% and above.
- An android application was implemented for farmers to detect rice leaf diseases quickly and easily.
- The use of digital images for disease detection has several advantages over traditional methods, including early detection and non-invasive techniques.
- The android application can improve rice production and reduce yield losses, while the model can be utilized by researchers and agricultural experts.
- The proposed model and application offer a valuable contribution to the field of deep learning and agriculture.
- This thesis provides a reliable and efficient tool for the detection of rice leaf diseases, potentially contributing to sustainable agriculture and food security in the Indian subcontinent.

Further Scope

- A larger and more diverse dataset can be used having images with high resolution images can be used and the model's performance can be optimized using hyperparameter tuning and use of transfer learning model like VGG16 and VGG19
- Integrating the model with other technologies like IoT sensors or drones can provide more accurate and real-time data for disease detection and management for mechanized farming over large farm fields.

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