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REVIEW OF APPLICATION OF SMART IMAGE PROCESSING AND TRANSFER LEARNING FOR RICE DISEASE AND NUTRITIONAL DEFICIENCY DETECTION

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Abstract - *In agriculture, the early detection of crop diseases and nutritional deficiencies is critical for ensuring food security and crop yield optimization. This paper presents a novel approach using smart image processing and transfer learning in Python to address the specific challenge of rice disease and nutritional deficiency detection. The system employs a Python-based image processing framework, supplemented by a diverse dataset of rice plant images, including healthy plants, plants afflicted with various diseases, and plants with nutritional deficiencies. MobileNetV2, combined with transfer learning techniques, forms the core of the paper, enabling accurate and efficient classification of rice plant health. The system is designed with a user-friendly graphical user interface (GUI), making it accessible to a wider audience. This paper offers a promising solution to support farmers in identifying and mitigating crop health issues in a timely manner, thereby contributing to agricultural sustainability.*

Key Words: **Smart agriculture, Image classification, Rice Disease Detection, Nutritional Deficiency Detection.**

1 INTRODUCTION

Rice, a staple food for over half of the global population, plays a pivotal role in addressing the nutritional needs of billions. However, rice cultivation faces a constant threat from diseases and nutritional deficiencies that can significantly affect crop yield and quality. Traditional methods of detection are often time-consuming and labor-intensive. To address this issue, our paper introduces an innovative approach that combines smart image processing and transfer learning in a Python-based system to swiftly and accurately detect diseases and nutritional deficiencies in rice plants.
The foundation of our system is a diverse dataset of rice plant images, which includes various health states, ranging from pristine to those affected by diseases and nutritional deficits. We employ MobileNetV2, a deep learning architecture, and transfer learning, leveraging pre-trained models to harness the power of image classification. This approach allows for precise identification and classification of rice plant health conditions, enabling early intervention and disease management.
To enhance accessibility and usability, our system is equipped with a simple and intuitive graphical user interface (GUI). This makes it feasible for farmers and agricultural professionals to utilize the technology without extensive technical expertise.

1.1 MACHINE LEARNING

Machine learning is a computational process that produces a particular outcome without being explicitly programmed. These methods adapt themself by learning from experience to produce a better outcome. This learning from experience is the training process, where input data is given together with the desired outcome. Machine learning is a field of computer science that is concerned with developing algorithms and models that enable computers to learn from data and improve their performance on a given task over time. The machine learning model then learns itself to link the input data to the desired outcome. This is done in a way that not only the training data can be identified, but also new, previously unseen data.
In essence, machine learning is a way of teaching computers to make predictions or decisions based on examples, without being explicitly programmed to do so.
There are several types of machine learning algorithms, including supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the algorithm is trained on a labelled dataset, where each example is associated with a corresponding label or target value. The goal of the algorithm is to learn a mapping from the input features to the output label, such that it can accurately predict the label for new, unseen examples. Examples of supervised learning are logistic regression, decision trees (DTs), and support vector machines (SVM).

In unsupervised learning, the algorithm is trained on an unlabeled dataset, where there are no corresponding target values. The goal of the algorithm is to find patterns or structure in the data, such as clusters or latent variables. Examples of unsupervised learning are hierarchical clustering, k-means, and k-nearest neighbors (K-NN).
Then there is also a category called semi-supervised learning. Here, only part of the data is labelled. In this situation, the labelled data can be used for the learning of the unlabeled part. Examples of semi-supervised learning are expectation maximisation (EM) with generative mixture models, cotraining, and transductive SVM.
In reinforcement learning, the algorithm learns to make decisions based on feedback from the environment. The algorithm receives a reward or penalty for each action it takes, and its goal is to learn a policy that maximises the cumulative reward over time.
One of the key advantages of machine learning is its ability to automate complex decision-making tasks that are difficult for humans to perform manually. For example, machine learning can be used to detect fraud in financial transactions, predict customer churn in marketing, or diagnose diseases in medical imaging.

1.2 IMAGE PROCESSING

Image processing is a field of study that focuses on analysing, manipulating, and enhancing digital images using various algorithms and techniques. It involves applying mathematical operations and computational methods to images to extract meaningful information, improve visual quality, and enable automated analysis.

Digital images are composed of discrete pixels, where each pixel represents a specific colour or intensity value. Image processing techniques can be applied to both two dimensional (2D) images and three-dimensional (3D) images, such as volumetric data from medical imaging.

The primary goals of image processing include:

Image Enhancement: Techniques to improve the visual quality of images by reducing noise, enhancing contrast, adjusting brightness and colour balance, and removing artefacts.

Image Restoration: Methods to recover degraded or damaged images caused by factors like motion blur, noise, or compression artefacts.

Image Compression: Algorithms for reducing the size of image files to optimise storage space and facilitate efficient transmission over networks without significant loss of visual quality.

Image Segmentation: The process of partitioning an image into meaningful regions or objects to facilitate further analysis or understanding of its contents.

Feature Extraction: Methods for extracting relevant features or characteristics from images, such as edges, corners, textures, or shapes, which are essential for subsequent tasks like object detection and recognition.

Object Detection and Recognition: Techniques to identify and localise specific objects or patterns within images, enabling automated analysis, classification, or tracking.

1.3 CLASSIFICATION OF DISEASES AFFECTING RICE PLANTS

Plant diseases are of two types biotic and abiotic. Diseases reveal some similar sets of characteristics in various plant parts. Some characteristics are local to certain parts of the field, and others may spread over an entire group of areas. This characteristic analysis plays a significant role in plant disease detection and future diagnosis. Characteristics of plant disease and deficiency symptoms can be described as follows.

1.3.1. Rice blast : The symptoms of rice blast include lesions that can be found on all parts of the plant, including leaves, leaf collars, necks, panicles, pedicels, and seeds. However, the most common and diagnostic symptom, diamond-shaped lesions, of rice blast occur on the leaves. Here we have considered three kinds of rice blast disease: apex blast, leaf blast, and neck blast.

1.3.2. Bacterial blight: Rice bacterial blight is caused by the bacterium Xanthomonas oryzae PV. Oryzae. The initial signs of rice with bacterial leaf blight are water soaked lesions at the edges and toward the tip of the leaf blades. Lesions grow larger and release milky sap that dries and turns a yellowish colour. This is followed by characteristic, greyish-white lesions on the leaves. This last stage of infection precedes the drying out and death of the foliage within 2–3 weeks.

1.3.3. Brown spot : Brown spot disease of rice is caused by the fungus Helminthosporium Oryzae. The period of infection can be from the seedling to the milking stage. The disease first appears as minute brown dots and later becomes cylindrical or oval to circular on leaves. The yield loss can be 50% of the total attainable production in severe cases.

1.3.4. Stem rot : Rice stem rot is a fungal disease caused by the pathogen Sclerotium oryzae. This disease affects water-sown rice plants and usually becomes noticeable in the early tillering stage. Symptoms begin as small, rectangular black lesions on the leaf sheaths at the waterline of flooded rice fields.

1.3.5. Leaf burn : Rice leaf burn is a fungal disease caused by Alternaria Padwickii. Symptoms appear on leaves and ripening grains. Circular to oval spots with dark brown margins appear on the leaves. These spots show many light brown to white spots at the centre of the leaves.

1.3.6. Leaf smut : Leaf smut is caused by the fungus Entyloma Oryzae. The fungus creates angular black spots on both sides of the leaves. Heavily infected turns yellow and leaf tips turn to die and turn grey. This appears in the late growing season and causes loss .

1.3.7. Rice tungro virus : This is caused by the Rice tungro bacilliform virus. Plants affected by tungro show stunting and reduced tillering. Leaves become yellow or orange-yellow; they may also develop rust-coloured spots. Discoloration can be seen from leaf tip to blade.

1.4 RICE DISEASE AND NUTRIENT DEFICIENCY DETECTION

Around 9% of crop and livestock production is lost annually due to disease and pests worldwide. Farmers lose more than 6 billion USD every year in India due to crop disease and pest attacks. Plant disease is responsible for approximately 15–25% loss of agricultural products in countries like India.

Plant disease and deficiency detection require on-field diagnosis in a stipulated time to save the crop. In the current era of digital agriculture, conventional plant disease detection by visual inspection and laboratory-based analysis methods appear time-consuming and laborious. Sometimes disease detection based on visual inspection includes bias, misconceptions, and errors; making it difficult for inexperienced and young farmers. Consequently, the detection of plant diseases and nutrient deficiencies needs expert staffing. It is also difficult to detect the nutrient deficiency symptoms and differentiate them from diseases due to shared symptoms, especially in standing water conditions in transplanted rice fields. Therefore, there is a pressing demand for an accurate and rapid diagnosis of plant diseases to lessen quantitative and qualitative losses.

Imaging systems perform better than non-imaging systems for plant disease detection. So far, much of the research on plant disease detection and crop health monitoring has been done on unmanned aerial vehicle (UAV) image processing and satellite imaging techniques. UAVs usually cover a large area in a short time; however, the chances of error are generally more due to low-resolution and noise-prone images. Using UAVs for the aerial survey also needs permission from governing bodies in certain countries and locations. The cost incurred in the entire process becomes prohibitively high. These methods are also climate-dependent and need expert supervision for complete decision-making. Hence, the procurement of UAVs and high-resolution imagery for small farm holders in developing countries has become economically impractical. Hence, a climate and location-independent, low-cost, affordable, and high-resolution imaging device can solve these problems.

2. LITERATURE REVIEW

1] Sharma, Mayuri, et al. In this study the author proposes a framework of hosting high end systems in the cloud where processing can be done, and farmers can interact with the cloud-based system. With the availability of high computational power, many studies have been focused on applying convolutional Neural Networks-based Deep Learning (CNN-based DL) architectures, including Transfer learning (TL) models on agricultural research. Ensembling of various TL architectures has the potential to improve the performance of predictive models to a great extent. In this work, six TL architectures viz. InceptionV3, ResNet152V2, Xception, DenseNet201, InceptionResNetV2, and VGG19 are considered, and their various ensemble models are used to carry out the task of deficiency diagnosis in rice plants. Two publicly available datasets from Mendeley and Kaggle are used in this study. The ensemble-based architecture enhanced the highest classification accuracy to 100% from 99.17% in the Mendeley dataset, while for the Kaggle dataset; it was enhanced to 92% from 90%.

2] Talukder, et al. In this research, the authors have proposed a robust Deep Ensemble Convolutional Neural Network (DECNN) model that can diagnose rice nutrient deficiency with high accuracy. Different pre-trained models named InceptionV3, InceptionResNetV2, DenseNet121, DenseNet169, and DenseNet201 are reformed by adding various layers, and their diagnostic accuracy is observed on the Kaggle dataset. Using appropriate data augmentation, a proper dense layer, a pooling layer, and a dropout layer, each of the models improves its prediction accuracy, precision, recall, and F1 score. Among the five modified pretrained models, the modified DensNet169 model provides the highest test accuracy, which has improved from 92% to 96.66%.

3] Orchi, et al. In this paper, the authors provide a general survey of several studies conducted and methods used with their advantages and disadvantages over the past decade in the field of plant disease recognition using image processing techniques, deep learning, transfer learning, hyperspectral image analysis, machine learning and IoT systems. Also, this survey presents the challenges to be overcome in the process of automatic identification of plant diseases. Therefore, these gaps that need to be filled form the basis for future work to be undertaken and which we will discuss later.

4] Qiang,et al. In this paper, the authors consider various machine learning and deep learning techniques (transfer learning) for rice disease detection. In this study three different rice diseases viz. bacterial blight, rice blast, and brown spot are considered. A detailed comparative analysis of the results indicates the superiority of transfer learning techniques over conventional machine learning techniques. It is observed that InceptionResNetV2 achieves the best result followed by XceptionNet.

5] Gautam, Vinay, et al. In this paper, the authors proposed a model that was concerned with the biotic diseases of paddy leaves due to fungi and bacteria. The proposed model showed an accuracy rate of 96.4%, better than state-of-the-art models with different variants of TL architectures. After analysis of the outcomes, the study concluded that the anticipated model outperforms other existing models.

6] Elakya, R., et al. In this paper, the authors will give a quick overview of what trends were used in deep learning for the prediction of disease and pest attacks in food crops. We have reviewed a few papers and analysed that recent advances in deep transfer learning and applying convolutional neural network pre-trained algorithms give an effective and practical solution for this problem.
7] Hussein, Osama Alaa, et al. In this paper, the authors have focused on deep learning. Using the convolutional neural network algorithm, one of the most tested algorithms for its accuracy and flexibility in dealing with different types of classifications, the learning transfer techniques that save a lot of time and effort are bypassed, and we have used more than one type of transfer learning. A data augmentation technique has also been used, which helps to achieve good results. Three sets of databases were used for different rice diseases. We have four categories of diseases, for example (bacterial leaf blight, brown spot, LeafBlast, and Hispa).

8] Joseph, et al. In this paper, the authors stated that this review can help the researchers to get a brief overview of how state-of-the-art CNN models can be used for disease diagnosis in plants, and an overview of the state-of-the-art studies that have used visualisation techniques to identify the disease spots for better diagnosis. The review also summarises the studies that have used hyperspectral images for plant disease diagnosis and various data sources used by different studies. The challenges that currently exist while developing a plant disease diagnostic system and the shortcomings and open areas for research have also been discussed in this manuscript.

9] Ngugi, et al. In this paper, the authors provide a comprehensive review of recent studies carried out in the area of crop pest and disease recognition using image processing and machine learning techniques. We hope that this work will be a valuable resource for researchers in this area of crop pest and disease recognition using image processing techniques. In particular, we concentrate on the use of RGB images owing to the low cost and high availability of digital RGB cameras. We report that recent efforts have focused on the use of deep learning instead of training shallow classifiers using hand-crafted features.

10] M. V. Applalanaidu, et al. In this paper, the authors have conducted a systematic literature study on the applications of the state-of-the-art ML and DL algorithms such as Support Vector Machine (SVM), Neural Network (NN), K-Nearest Neighbor (KNN), Naïve Bayes (NB), other few popular ML algorithms and AlexNet, GoogLeNet, VGGNet, and other few popular DL algorithms respectively for plant disease categorization. Each stated algorithm is characterised through the corresponding processing methods such as image segmentation, feature extraction, along with the standardised experimental-setup metrics such as total number of training/testing dataset employed, number of diseases under considerations, type of classifier utilised, and the percentage of classification accuracy.

3. METHODOLOGY

The proposed system is an advanced agricultural solution that integrates smart image processing, transfer learning, and a user-friendly graphical user interface to detect and classify diseases and nutritional deficiencies in rice plants. Leveraging Python-based image analysis and a diverse dataset of rice plant images, the system employs MobileNetV2 architecture with transfer learning to provide accurate, real-time health assessment. Its intuitive interface ensures accessibility to farmers and agricultural professionals, enabling proactive management of crop health, thus contributing to increased crop yields and global food security.

3.1 SYSTEM ARCHITECTURE

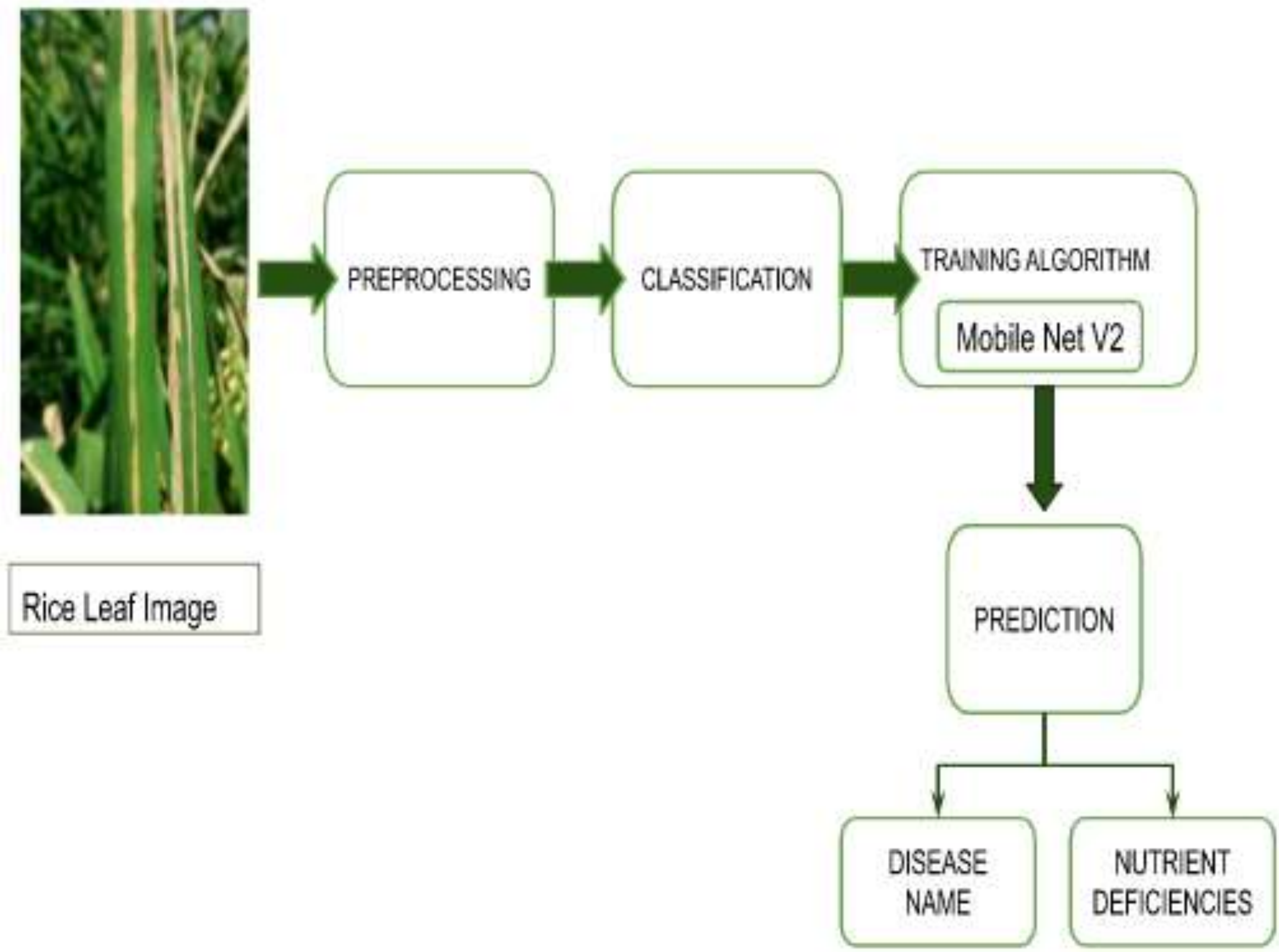

Fig 3.1 Shows the Architecture Of Proposed System of Project

3.1 WORKING

Step 1: involves importing necessary libraries such as PIL for image processing, Torch for deep learning functionalities, Tkinter for GUI creation, and Pickle for object serialisation.

Step 2: initialises the GUI page, setting up the Tkinter window layout for image browsing.

Step 3: initialises the GUI page, setting up the Tkinter window layout for image browsing.

Step 4: creates a function to browse the image of a rice plant from the dataset, utilising a file dialog to select the image file.

Step 5: involves utilising MobileNetV2 with Transfer Learning for predicting diseases and nutrient deficiencies in rice plant leaves. This step includes loading a pre-trained MobileNetV2 model and performing transfer learning for fine-tuning on the dataset.

Step 6: concludes with the successful prediction output, displaying the result of the prediction model applied to the selected image. This output indicates a deficiency in potassium nutrient within the rice lea

3.3 FLOW CHART

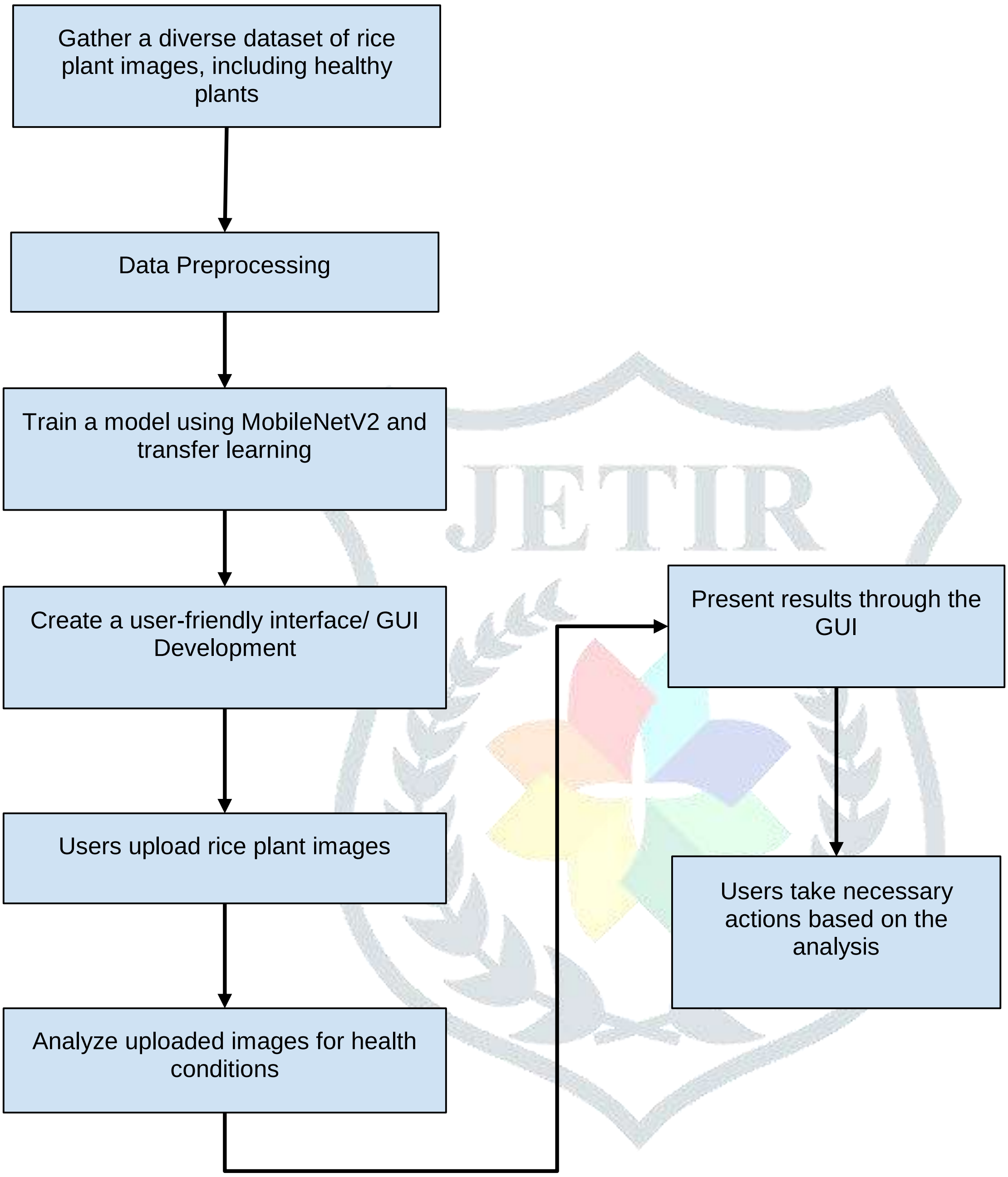

Fig 2. Shows the Flow chart Of Proposed System of Project

4. RESULT

The project has been successfully implemented, leveraging smart image processing techniques, transfer learning methodologies, and a user-friendly graphical user interface. Utilising the MobileNet V2 training algorithm, our system is capable of detecting and classifying both diseases and nutritional deficiencies in rice plants.

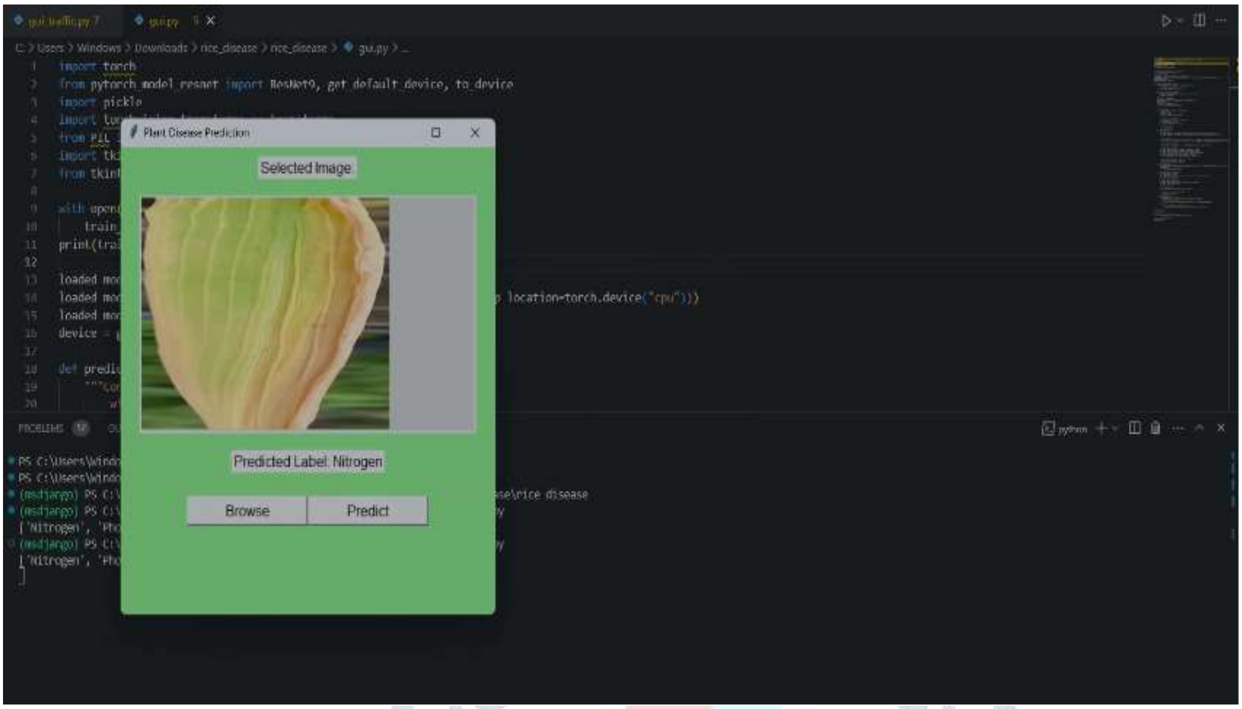

Fig 5.7 shows the Nutrient Deficiencies of Nitrogen

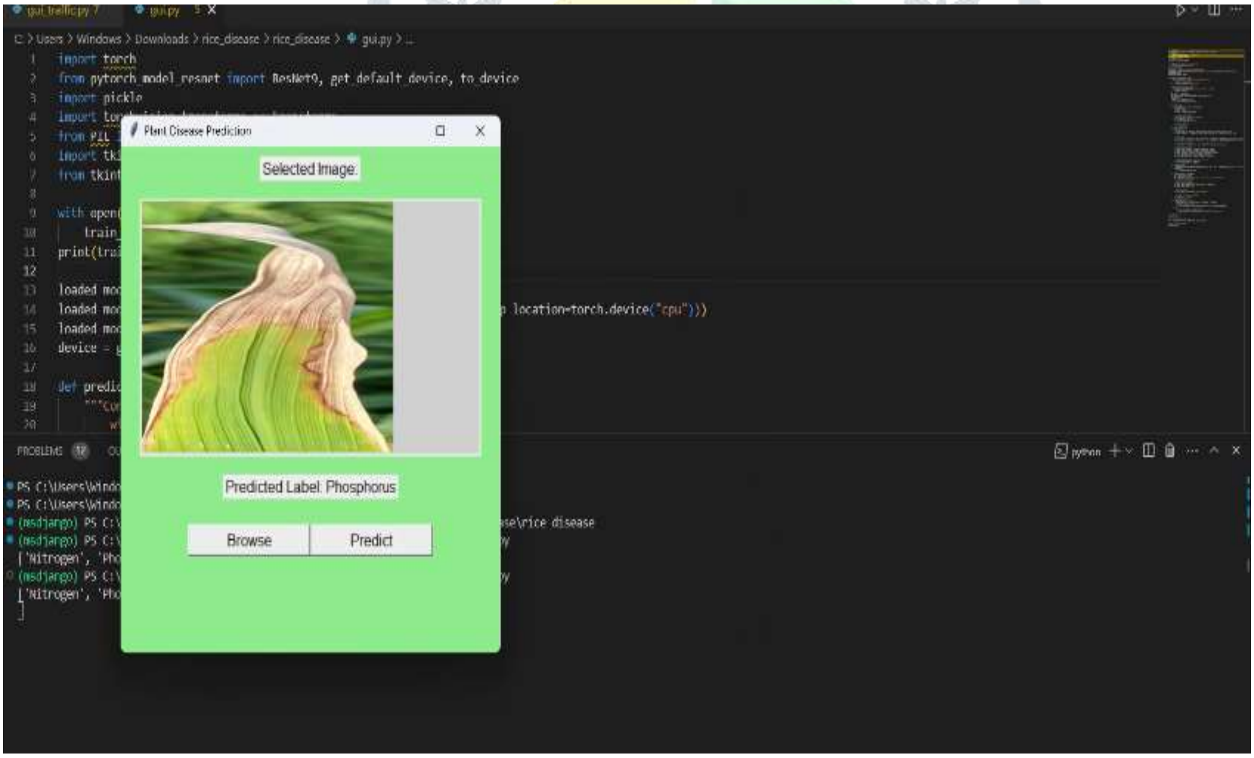

Fig 5.8 shows the Nutrient Deficiencies of Phosphorus.

5. CONCLUSIONS

As agriculture continues to face increasing demands and environmental pressures, this innovative solution not only benefits rice cultivation but also sets a precedent for the application of technology in other crop sectors, contributing to the broader goals of food security and sustainable agricultural practices. The implementation of our smart image processing and transfer learning system for rice disease and nutritional deficiency detection represents a significant advancement in agricultural technology. By enabling early identification and classification of health issues in rice plants, we empower farmers to take proactive measures, leading to increased crop yields, improved food security, and sustainable agriculture. The user-friendly interface ensures accessibility and usability, making this system a valuable tool in the hands of those responsible for feeding a growing global population.

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