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A Critical Investigation on Disease Detection of Oryza Sativa (Rice) Using Image Processing Techniques

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***Abstract**: -* Rice is the most essential part of food intake in daily bias, which is single of the furthermost essential food sources for most of the world's population. In such conditions, farmers struggle to identify disease in Rice leaf in the premature stage. This article describes the development of a copy acquisition application for rice leaf disease and image processing algorithms to determine the acute intensity of the disease. The pictures were acquired using the developed system and processed using MATLAB software. By quantifying the total and infected leaf area based on pixel-counting, the algorithm calculated the percentage of the infected leaf area using a ratio-based method. The study achieved a range of 15.53% to 41.23% of the total percentage of infected leaf area through the image processing method. In comparison, the leaf area meter method yielded a lower range of 23.49% to 28.98% of the total infected area. This implies the image-processing approach can capture a wider extent of infection. However, a deviation was observed between the two methods, ranging from -9.39% to 17.74% in the results of image processing. It explores the detection of diseases in rice plants, aiming to enhance accuracy, efficiency, and timeliness in disease management. Implementing this technology significantly benefits the agricultural sector by enabling early intervention, reducing crop losses, and promoting sustainable farming practices.

***Keywords**: Rice leaf disease, Disease quantification, Image Processing, Detection Algorithm.*

1. Introduction

Oryza sativa (Rice) is the most widely obsessed food for most of the world's population. Its cultivation is critical for global food security. However, paddy cultivation is often hampered by various leaf diseases caused by pathogens including fungi, bacteria, and viruses, which lead to substantial reductions in yield and quality. Studies indicate an average yield loss of 9.9% due to paddy leaf diseases, highlighting the need to manage strategies according to the disease to ensure profitable harvests and sustainable production.

Machine Learning is the field that allows software applications to predict outcomes in the future by examining patterns from data. Machine learning is an artificial intelligence (AI) application that permits the procedure to learn and progress from practice without being clearly programmed automatically. By creating the Computer Program which can develop or change itself when it is fed with new data, this ability of the computer to mend only some basic parts gets termed as a Learning Algorithm.

In the process, predict the use of specialized algorithms and train them in a certain way. It feeds the existing data to the algorithm, and in this process, we use this trained data in a particular algorithm to give predictions on newly implemented data. Machine learning is divided into three categories. They are supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, we give the stored data and the subsequent tagging to learn data that must be labeled by the user. Unsupervised learning has no labels. It showcases the learning algorithm. This algorithm must reckon out the grouping of the input data. Lastly, Reinforcement learning animatedly cooperates with its capitals and receipts positive or negative response to progress its working.

1.1 Image processing for Diseased-Leaf Detection: The image-processing techniques are presented and promise to address the following challenges

For instance, a real-time variable-rate chemical spraying system using chromatic aberration-based image segmentation demonstrated a significant reduction in chemical use by 33.88% compared to constant-rate application. Similarly, to diagnose and quantify paddy leaf diseases with high accuracy, numerous revisions are undertaken into consideration from different image processing techniques.

Larijani et al. utilized RGB images captured by a quadcopter, processed using Otsu's method, K-means clustering, and KNN classification, achieving an overall accuracy of 94%. Ibrahim et al. applied color moments, GLCM, and region props for feature extraction and used SVM for classification, achieving 86.25% accuracy. Matin et al. employed AlexNet CNN for detecting rice leaf diseases, achieving over 99% accuracy with image augmentation techniques. Ramesh and Vydeki used HSV images and binary images for segmentation and a DNN with Java Optimization Algorithm for classification, achieving accuracies between 90.57% and 98.9%. Pal employed CNN and pre-trained models, with ResNet-50 achieving the definiteness of 96.27%. Saha and Ahsan used a GLCM and RF classifier machine, achieving 92.77% accuracy. Upadhyay and Kumar used a two-phase CNN approach, achieving 99.20% accuracy. Kiratiratanapruk et al. used YOLOv4 for object detection and image tiling, improving prediction performance to 91.14%. Archana et al. utilized a modified K-means algorithm and achieved high accuracies for multiple diseases using various feature extraction techniques.

The primary aim of this research is to assess the severity level of paddy leaf disease using an automated real-time image processing technique. Specific objectives include:

Development of an Image-Acquisition System: Construct a system capable of capturing high-quality images of paddy leaves under controlled lighting conditions.

Image Processing Algorithm Development: Develop an algorithm to analyze the captured images and accurately calculate the severity level of paddy leaf white tip diseases.

This research aims to provide an efficient, accessible, and accurate method for paddy leaf disease quantification, contributing to increased yield, reduced yield losses, and sustainable rice production.

1.2 Need for research in leaf detection: Economic & Agricultural Significance: Paddy (Oryza sativa L.) holds great economic and agricultural significance since it is the food for nearly half of the world's population. The health of paddy crops directly affects food security and the livelihoods of millions of farmers globally. However, paddy cultivation is often affected by the diseases of the leaves originating from a variety of pathogens such as fungi, bacteria, and viruses. These diseases can lead to significant yield losses, on average around 9.9%, which directly decrease the standard of the harvested grain. As a result, it is essential to control and prevent these diseases in a bid to realize stable and profitable production of paddy.

1.3 Limitations of Traditional Methods:

Traditional methods for detecting and quantifying paddy leaf diseases—such as visual inspection, laboratory analysis, and remote sensing techniques—present several limitations:

Time-Consuming and Costly: These methods are often labor-intensive and require significant time and financial resources.

Subjectivity and Expertise Dependence: The accuracy of visual inspections depends heavily on the expertise and visual acuity of the individual conducting the analysis, leading to potential inconsistencies.

Specialized Equipment and Facilities: Laboratory analyses and remote sensing techniques require access to specialized equipment and facilities, which may not be readily available, particularly in rural or resource-limited settings.

2. Literature Review

2.1 Theoretical survey:

Paddy (rice) is a vital food for half of the world's population. Diseases affecting paddy can significantly impact yield and quality, making disease detection a crucial aspect of rice cultivation. The following literature review provides an overview of the methodologies, technologies, and advancements in the field of paddy disease detection.

2.2 Traditional Methods of Paddy Disease Detection:

Traditionally, farmers or experts have detected paddy diseases through visual inspection. This method identifies symptoms such as leaf spots, discoloration, or deformities. Therefore, several restrictions are present in this approach:

Subjectivity and Expertise: Accuracy depends heavily on the inspector's expertise. Time-Consuming: Manual inspection of large fields is labor-intensive and time-consuming.

Delayed Detection: Diseases are often detected only after significant damage has occurred.

2.3 Imaging and Spectral Analysis:

The present advancements have shifted for automated and semi-automated methods using imaging technologies:

Visible and Near-Infrared (NIR) Imaging: Studies such as Mahlein et al. (2012) have utilized spectral imaging to detect disease symptoms not visible to the naked eye. This method can show the clear difference between healthy and diseased plants based on spectral reflectance.

Thermal Imaging: Thermal cameras detect temperature variations caused by disease-related changes in plant physiology. For instance, Chaerle and Van Der Straeten (2000) demonstrated that thermal imaging could identify stress responses in plants before visible symptoms appear.

2.4 Machine Learning and Computer Vision:

The integration of machine learning (ML) and computer vision (CV) techniques has revolutionized paddy disease detection: Convolutional Neural Networks (CNNs): CNNs have shown high accuracy in image-based disease detection. For example, Mohanty et al. (2016) developed a CNN model that achieved over 99% accuracy in classifying 26 diseases in 14 crop species, including rice.

Support Vector Machine (SVMs): These are used in classifying tasks in disease detection. In a study by Pujari et al. (2016), SVMs were applied to detect and classify paddy diseases with substantial accuracy.

Deep Learning Frameworks: Advanced frameworks like TensorFlow and PyTorch facilitate the implementation of robust models for disease detection. Et al Zhang (2018) used a deep-learning approach to identify rice diseases from images, achieving high precision and recall rates.

2.5 Remote Sensing and UAVs: Unmanned Aerial Vehicles (UAVs) are a combination of high-resolution cameras & sensors that offer a modern approach to monitoring large paddy fields:

Drone-Based Surveillance: In this process, detailed images can be collected from vast areas, which are further implemented using ML algorithms to identify diseased patches. A study by Sankaran et al. (2015) highlighted the efficiency of drones in agricultural monitoring.

Multispectral and Hyperspectral Imaging: UAVs can be equipped with multispectral or hyperspectral sensors to capture data across various wavelengths, enhancing the detection of subtle disease symptoms. Yang (2020) demonstrated the procedure of applying hyperspectral imaging in early disease-detection in rice fields.

2.6 Internet of Things (IoT) and Sensor Networks: IOT technology integrates various sensors and devices to monitor environmental conditions conducive to disease development:

Environmental Sensors: Sensors measuring humidity, temperature, and soil moisture can predict disease outbreaks based on favorable conditions. Li et al. (2018) developed an IoT-based system for real-time monitoring and disease prediction in paddy fields.

Wireless Sensor Networks (WSNs): WSNs facilitate the collection and transmission of data from remote fields to central processing units. This data is analyzed to detect disease patterns and provide timely alerts to farmers.

2.7 Challenges and Future Directions: Despite significant advancements, several challenges remain:

Data Quality and Availability: High-quality annotated dataset is required for training accurate models. The limited availability of such datasets can hinder progress.

Generalization and Robustness: Models need to generalize across different environments and conditions. Ensuring robustness to varying field conditions remains a challenge.

Integration and Scalability: Integrating various technologies into a cohesive system that can be scaled for large agricultural operations is complex.

2.8 Future research should focus on:

Developing more Comprehensive Datasets: Collaborative efforts to create large, annotated datasets covering diverse disease symptoms and environmental conditions.

Enhancing Model Interpretability: Improving the transparency of ML models to provide actionable insights to farmers.

Real-Time Monitoring Systems: Advancing real-time disease monitoring and alert systems using IoT and edge computing devices.

3.Identification of Rice Disease:

One of the vitally natural variables in any crop is that reduces crop yields due to diseases if not dealt with promptly. Plant diseases should be detected and identified in the early phase as a vital part of precision agriculture (1). The people in India mostly depend on rice as food. By such means, they cultivate the rice crop (2). However, the productivity of rice is reduced to 10 to 15 percent due to diseased crops every year in India [3]. To prevent damaged crops, we require continuous monitoring techniques. That is still in the practice of detecting,

These diseases are mostly observed with the naked eye. It is not easy to monitor huge fields constantly by farmers. Automated disease detection is used to recognition help farmers in taking care of crops (4). In recent times, computer observation (5), pattern identification (6), and image processing (7) must aid a lot to agriculture.

Image processing techniques have a huge role in plant disease detection cost-effectively while executing in less time. Normally, it is noticed that both machine learning and digital image processing together are the basic structure of disease detection systems in crops. The basic perspective on plant disease detection using machine learning and digital image processing is shown in Figure 1.

The image collection is used to gather infected and fine leaf samples of different plants. Infected leaves are accumulated from any on-site data set or directly collected from the field. In image processing, the first step is to cleanse the copy to get value of the copy. The next important process is data cleaning to find the precision of the disease and recognize the model (Figure 2). It majorly depends on the eminence of the dataset. Further, Image segmentation is managed to classify diseased parts of the leaf sample. There are many extracts relevant to image processing that are collected from the dataset. Deep learning is an vital aspect in the involuntary descent of attributes that are undoubtedly relayed to derive key information from an accurate amount of image dataset. Deep learning also loose change according to human explanation while implementing the conventional in machine learning, as well.

as improvement has also occurred and supplied in the zone of image classification and other functions (8).

Figure 1: Basic format of crop disease detection.

[Source: Early-Stage Brown Spot Disease Recognition in Paddy Using Image Processing and Deep Learning Techniques]

The brown spot appears basically as a small brown dot and further takes on a round or cylindrical shape to an oval shape. There are high chances of brown spots spreading in nutrient-deficient soils. It can be spread by the organism called Helminthosporium oryzae, which affects the plant from seedling in the nursery to the milky stage (9). A sample of brown spot diseased rice life is spotted in Figure 6.

In the initial phase, they partitioned a dataset depending on disease severity, including healthy leaf and those with brown spot (BS), leaf smut (LS), and bacterial leaf blight (BLB), using 4000 images for each class. The second phase is a CNN architecture that achieves a classified exactness of 99.20%. Kiratiratanapruk et al(10) have developed a detection system for 8 rice leaf diseases by the CNN object detection and image tiling. The leaf width is estimated from the images and used to divide the image into sub-images with similar size objects. They trained a YOLOv4 model on the new image dataset and improved the prediction performance from 87.56% to 91.14%. Another study by Archana etal. (11) proposed a method for rice plant image analysis, which utilized a modified K-means segmentation algorithm.

Different types of rice leaf diseases affect the growth of plants and productivity. The major categories of diseased rice leaf are categorized into two types of nursery diseases and main field diseases. The nursery diseases are again divided into three types such as blast(pyriculariagrisea), bacterial leaf blight, and rice tungro-disease (RSTV) (12). The main field diseases are further divided into six types such as brown spot, sheath rot, sheath blight, false smut, grain discoloration, and leaf streak. Blast is a foliage-disease, symptoms also occur in other plant parts.

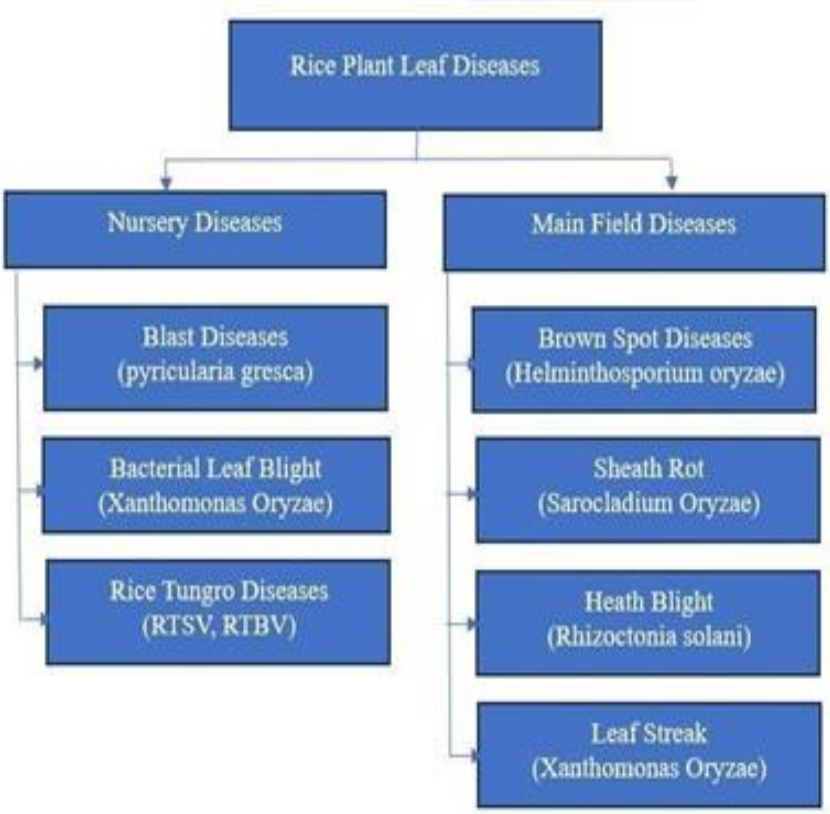

Figure 2. Paddy (Rice) Leaf Disease

[Source: Detection of paddy crops diseases and early diagnosis using faster regional CNN]

The nursery blast diseases were occurring on decomposed roll neck, and it was reported from 80 different countries. Blast disease can affect rice leaf at all different growth leaf stages and all airborne parts of the plant. Due to this disease, the expected grain loss is 70 to 80 percent. The bacterial leaf blight disease damages the seedling wilt or kresek. The damaged leaf looked like yellowish stripes on leaf blades, all lessons turned yellow color to white color as the disease advanced. Rice tungro disease affects the rice plant leaf by tungro exhibiting stunting and reduced tillering. All the affected rice leaves look yellow or orange-yellow and sometimes look rusty color spots. The symptom of damage is most panicles are sterile or partially filled grains.

The main field sheath blight disease symptom of damage is discussed as the rice leaf affected by tungro act, affected leaf becomes yellow color or orange-yellow color. Rice tiller is an inflorescence that is born on the uppermost internodes of rice plants. The sheath rot is caused principally by the fungus in some different cases sarocladium oryzae. In this leaf, the affected portion shows irregular spots and reddish-brown margins. The brown spot diseases occur on fungal blight or sesame leaf spots (13). It was isolated brown round to oval in the affected leaf and affected the 50% yield in some cases. In fig.1 shows different levels of rice leaf diseases, Leaf streak is extended by bacterial xanthomonas, and infected rice leaf show browning and drying of leaves. It affects mostly high temperatures and humidity and damages vegetative growing stage. Rice diseases are characterized by texture, shape, and color, which can also depend on the temperature.

Et al Orillo (14) developed a BPNN-based model that depends on identifying defective rice leaves. All implementations are done as an experiment in MATLAB. We have a dataset consisting of 134 defective leaf pictures in which two sets of random images are 20 which are separated for verification and testing other remaining images are used to implement in this model. To acquire the value image the author applied image enhancement. Later Image segmentation is used to withdraw the features from images. Completely, BPNN was fed with explicit features to enhance leaf disease. The result analysis was obtained with 100% accuracy. Gill and Rishi (15) offered an summary of IP techniques to discover and group plant diseases. They have argued the magnitude of image compression in disease identification. The importance of Otsu's thresholding techniques for clustering images into segments, the K-means algorithm is used to remove filters and crop the image and identify plant diseases compared to the existing disease dataset. Et al Patidar (16) utilized digital photos of defective leaf and normal leaf to train a residual neural network and diagnose the diseased part in rice plants. The accuracy of the 34-layer residual NN was 95.83 percent. To provide a productive rice leaf disease identification and classification system, Kumar and Upadhyay (17) proposed an methodology to uncover image-based disease in paddy crops using CNN architecture. The writers have presented two experiments, in which one is done without segmentation and the other is done with segmentation. Image segmentation was utilized to withdraw background unnecessary information from leaf images. CNN architecture is designed in such a way that 99.1% and 99.7% classification precision were realized in the disease detection without segmentation and disease detection with segmentation correspondingly.

Larijani et al., (18) experimented to diagnose rice blasts from canopy color IP techniques. They captured, resized, converted, and segmented RGB images of rice fields with a quadcopter and a digital camera. They detected and measured the disease spots with Otsu's method, K-means clustering, and KNN classification. They evaluated their algorithm and found that it has high sensitivity, specificity, and overall accuracy of 92%, 91.7%, and 94%, respectively (18).

The AlexNet (19) achieved over 99% accuracy, showcasing the effectiveness of their technique and image augmentation. Ramesh and Vydeki (20) extended an approach to distinguish and organize five types of paddy leaf diseases from farm field images. They converted RGB images to HSV images and used binary images to separate diseased and non-diseased parts. They segmented the images using K-means clustering and classified the diseases using a DNN with Java Optimization Algorithm (DNN_JOA) and achieved high accuracy ranging from 90.57% to 98.9% for different diseases. Pal (21) established a system to detect five types of paddy leaf diseases using CNN and pre-trained models. He converted RGB images to HSV, segmented them, extracted features using CNN, and classified them using ReLU and found that ResNet-50 has the highest accuracy (96.27%) and F1 score (98.19%) among the models.

Another study by Archana et al [22] proposed a method for rice plant image analysis, which utilized a modified K-means segmentation algorithm. The system extracted color features using the NIBCFE method, texture features using GLCM and BPF, and shape features by determining the area and diameter of infected portions. Their proposed method involves acquiring images with a digital camera under controlled lighting, filtering noise, segmenting for diseased regions, and extracting features, achieving final accuracies of 95.20%, 99.20%, 97.60%, and 98.40% for bacterial leaf blight, healthy leaves, brown spot, rice blast classification, respectively.

3.1 Advancements in Image Processing:

Recent technological advancements in image processing offer promising alternatives to traditional methods. These techniques provide several benefits:

Accuracy and Precision: In this IP techniques can provide consistent and objective assessments, reducing the variability introduced by human error.

Efficiency: Image processing can rapidly analyze large volumes of data, enabling real-time disease monitoring and management. Cost-Effectiveness: Once developed, following systems can reduce the reliance on expensive laboratory facilities and specialized personnel.

Environmental Impact: Precise disease quantification can lead to more targeted chemical treatments, reducing the overall use of agrochemicals and mitigating their negative environmental and health impacts.

3.2 Conceptual Model:

In this conceptual model identifying the rice leaf diseases based on IP techniques involves several key stages.

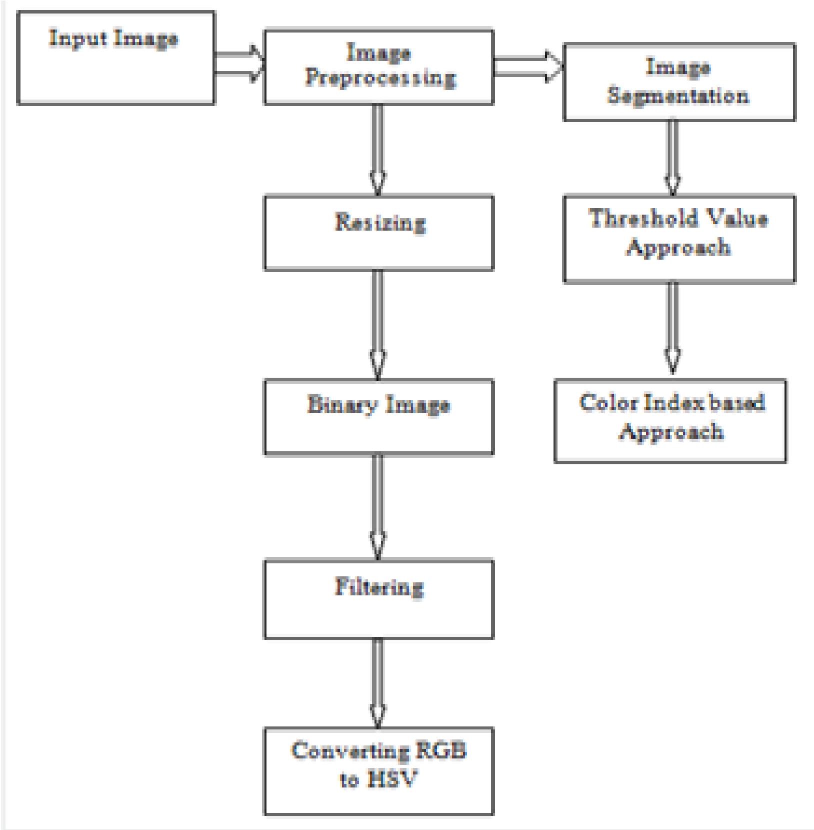

Figure 3: Conceptual Model

[source: https://www.researchgate.net/figure/Automatic-leaf-detection- of-plant-disease-using-image-preprocessing-and- segmentation_fig1_327222832]

In this model, we collect the input images and consider them for image processing. And follow these stages to get accurate outcomes.

4.Materials and Methods:

4.1 Design Consideration:

The proposed automated cart design places a strong emphasis on crucial factors for optimal functionality in paddy cultivation. It is adept at navigating diverse planting configurations by accommodating varying distances between rows and hills. The cart is designed with consideration for paddy plant height, strategically positioning the image acquisition system to effectively capture complete plant images. Special features are incorporated to address diverse lighting conditions, thereby enhancing image clarity. With a focus on robust load-bearing capacity, the cart supports both imaging equipment and the power source.

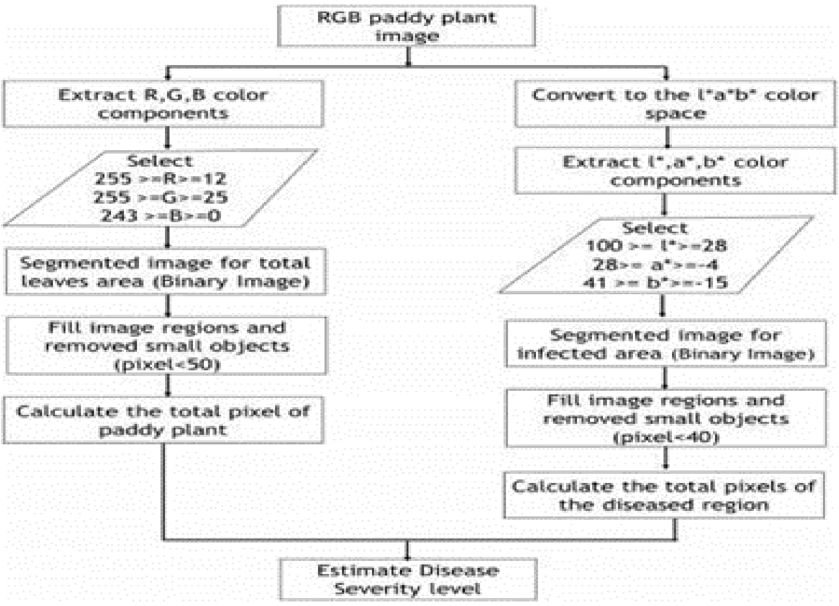

Figure 4: Block Diagram of IP workflow

[Source: https://www.journals.elsevier.com/smart-agricultural- technology]

The implementation of locally available materials is highlighted, facilitating easy replication and maintenance. Additionally, the lightweight design ensures energy efficiency and easy maneuverability across fields without causing soil compaction. In summary, this specialized solution offers efficiency in image acquisition for rice cultivation.

4.2 Leaf area measured using leaf area meter:

The LI-3100C Area Meter, a robust bench-top instrument, was used to precisely measure leaf area for comparison with image analysis methods. Following image acquisition through the automated cart, rice leaves were meticulously collected from the plants. Subsequently, the collected leaves underwent careful examination to distinguish between defective and fine sections.

The separated leaf portions, representing both healthy and diseased segments, were then transported to the laboratory for accurate measurement of their respective areas. The obtained data were diligently recorded to facilitate a thorough comparison with the image processing technology applied in the study.

Leaf Blast False Smut Bacterial Blight Leaf Strake Brown Spot

Figure 5: Types of diseases in Oryza sativa

[Source: https://www.researchgate.net/figure/Visual-symptoms-of- paddy-diseases_fig1_324526871]

4.3 Techniques

Visible Imaging Light Imaging:

Experiment Setup:

Objective: Evaluate the effectiveness of visible light imaging in detecting visible symptoms of paddy diseases.

Procedure: Collect images of paddy leaves infected with different diseases (e.g., bacterial leaf blight, rice blast). Use high- resolution cameras to capture images under consistent lighting conditions.

Analysis: Apply image processing techniques to highlight disease symptoms.

Use manual or automated methods to classify and quantify disease severity.

Results & Discussion:

- Visible light imaging can effectively identify diseases with distinct visual symptoms.
- Limitations include the inability to detect early-stage diseases or internal infections.

Figure 6: Brown spot disease in rice leaf.

[Source: https://www.researchgate.net/figure/Sample-images-of-leaf- diseases-for-rice_fig3_370340210].

5. Results and Discussions

5.1 Design of the image acquisition system:

These measurements played a crucial task in defining the dimensions of the structure. The length of the automated imaging system was 35.26 inches, the width was 11.75 inches, and the height was 37.78 inches.

5.2. Processed image:

The image processing workflow depicted in involves several stages for analyzing a paddy plant in MATLAB. The initial stage features the original color image of the paddy plant. Subsequently, a second image is generated using RGB representation, with specific regions masked out. Following this, a third image is created to highlight areas Infected with disease. Finally, the last image exclusively displays the regions of the paddy plant affected by disease. The overall pixel count is determined using the masked RGB image, while the defected area pixel count is calculated depending on the image highlighting disease-infected regions.

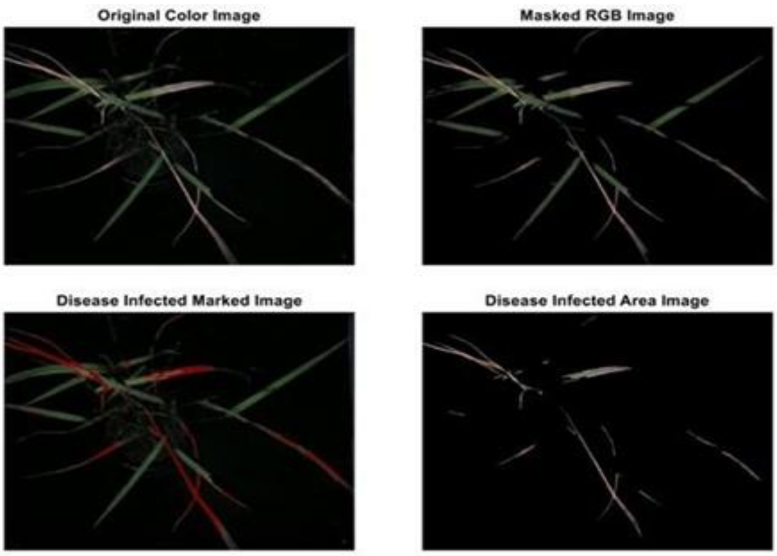

Figure 7: Image processing workflow for Rice leaves.

[Source: https://www.journals.elsevier.com/smart-agricultural-technology].

The integration in image-processing techniques, machine learning, and IoT in paddy disease detection marks a transformative shift in agricultural practices. By harnessing these technologies, we can move towards a future where precision agriculture becomes the norm, ensuring food security and promoting sustainable farming practices for generations to come.

6. Conclusion

The process begins with collecting a comprehensive dataset of rice plant images, which includes both healthy and diseased specimens. This dataset is annotated with expert knowledge to label the various diseases present. Using this labelled dataset, we train our machine learning models to recognize patterns and features associated with specific diseases. In conclusion, this project on detecting diseases in Oryza sativa plants using image processing techniques and machine learning algorithms represents a significant advancement in agricultural technology. The incorporation of these advanced technologies will have a constructive effect on crop management and hence increase yield, input efficiency, and food security. As we continue to refine our models and expand our datasets, the potential for even more accurate and efficient disease detection systems remains substantial, paving the way for a more sustainable and productive agricultural future

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