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Rice Leaf Disease Detection and Remedies using Deep Learning

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Abstract: This research provides a unique method using convolutional neural networks (CNN) for the automated diagnosis of four important rice leaf diseases: Leaf Blast, Leaf Blight, Tungro, and Brown Spot. The CNN model is trained using a dataset that includes pictures of both healthy and sick rice leaves, with training and testing conducted at an 8020 ratio respectively. When it comes to correctly determining if certain illnesses are present in rice leaves, the trained model performs admirably. Additionally, a user-friendly website interface is created so that users can upload pictures of infected rice leaves to diagnose diseases in real-time. After the diagnosis, the website offers customized recommendations categorized into 3 namely chemical pesticides, botanical pesticides, and biopesticides for treating the particular ailment found, which is a great help to farmers in properly maintaining crop health. By bridging the gap between cutting-edge technology and agricultural methods, this integrated system presents a viable way to increase the sustainability and production of rice crops attaining an accuracy of 98%.

Keywords: *Bacterial Leaf Blight, Brown Spot, Convolutional Neural Network, Leaf Blast, Tungro.*

1. Introduction

India is known as the "land of agriculture," as the sector employs a large number of people and is vital to our nation. One of the main variables influencing the state of our nation's domestic market is crop production. For agriculture to achieve sustainability and food security, plant/crop health is essential. However, a number of circumstances might cause the plants to quickly become infected with pathogens, which can lead to serious social and economic consequences. Crop infections are one of the most frequent causes of productivity loss since they can impact crop growth and development as well as crop yield and quality [5]. In order to prevent soil pollution, it is important to identify the disease and use certain pesticides as soon as possible [1].

Rice, serving as a vital food source for a significant portion of the global population, contends with a range of diseases that pose substantial threats to crop yield and food availability. Traditional methods of detecting and managing these diseases in rice cultivation often rely on labor-intensive manual approaches, resulting in delays in diagnosis and less effective treatment strategies[15]. However, the emergence of advanced technologies, particularly Convolutional Neural Networks (CNNs), presents promising opportunities to transform rice disease management practices. The CNN model is trained on a dataset of photos of rice leaves that are both healthy and diseased, and it achieves a high degree of accuracy in classifying diseases [1][6]. A user-friendly website interface is created to close the gap between cutting-edge technology and real-world application. Farmers may diagnose diseases in real time by uploading photographs of infected rice leaves to this website. When a user uploads an image, the website uses the trained CNN model to determine whether certain diseases are present and gives instant feedback on the diagnosis[7].In addition, the website provides customized suggestions for illness treatment and management, depending on the sickness that has been discovered. The objective of this integrated system is to equip farmers with the necessary knowledge and tools to improve agricultural productivity and control the health of their rice crops by making insights easily obtainable and actionable[11].This introduction establishes the groundwork for exploring the development, implementation, and assessment of the CNN-based rice disease detection and remediation system, highlighting its potential to bolster food security and mitigate yield losses in rice production.

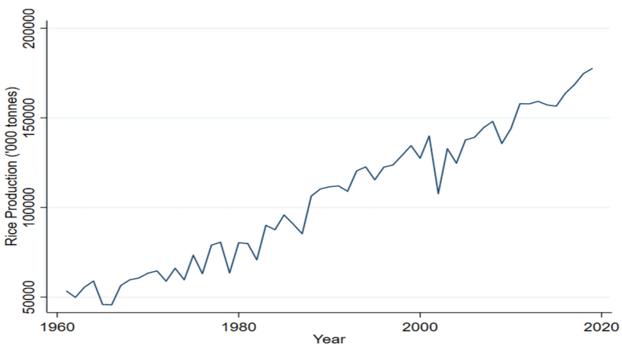

Fig.1.Graphical representation of Rice Production in India

The FAO states that it is built on 166 Mha of land, with an annual creation of 745.17 Mt of rice crop output and a usual profitability of about five T/ha. According to estimates, 880 metric tons of hard rice—a 70% increase—should be

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supplied by 2025 in order to meet the growing population requirement (as proposed by Lampe in 1995). In India, the entire 42.41 Mha area is dedicated to the cultivation of rice crops. In 2013, the usual efficiency of crop yield was 3.59 t/ha, with a year-wise creation of 104.40 mt of paddy crop. According to estimates, India will be able to produce 113 million tonnes of rice annually in 2021 to meet the country's growing food needs. It will take coordinated harvest and irrigation managerial innovations, as well as new cultivars, to achieve the increase in rice production. Ten major rice crop illnesses have led to a 10-15% reduction in the usual rice production, according to the analysts[4]. In light of this, it is now crucial to recognize the diseases that affect rice in order to ensure that it is produced in a way that is feasible.

In the days ahead, intelligent systems—which are learning-based and adaptable to various situations—are expected to be the most often utilized approaches. They improve the effectiveness of handling these kinds of circumstances.

The right conditions are provided by emerging technologies like artificial intelligence, computer vision, satellite photography, machine learning, and data analysis to create the environment required for smart farming[5]. In order to help farmers better control pricing and achieve high average crop yields, several technologies have been incorporated. Machine learning can only identify and diagnose pest insects and diseases affecting rice. Segmentation and preprocessing, feature extraction of different diseases and pest insects, and type recognition are the three steps involved in this technique. The techniques employed for the recognition phases have very high levels of detection and classification precision.

The literature survey highlights recent advancements in using machine learning and deep learning techniques for detecting and managing rice diseases. Papers from 2019 to 2023 showcase various approaches, including combining GLCM and statistical features with random forest for 92.77% accuracy, utilizing decision trees for 97.9167% accuracy, and employing CNNs for real-time disease detection. Innovative solutions like Rice Transformer integrate sensor and image data for 95% accuracy. Drone imagery emerges as a promising tool for early detection. A 2022 survey provides insights into deep learning techniques for plant disease diagnosis, while recent papers demonstrate high accuracy rates in automatic rice disease diagnosis. These contributions collectively enhance rice disease detection and management, fostering improved crop yield and food security.

2. Types of Disease

The rice plant encounters various diseases to name a few are Brown Spot, Bacterial Leaf Blight, Leaf Blast and Tungro, each presenting distinct challenges to crop health and productivity.

2.1 Brown Spot

A fungus called brown spot can infect both adult plants and seedlings. When seedlings are raised from extensively infected seeds, the disease can result in blight and 10–58% seedling loss.

Fig.2. Brown Spot

Brown spots on leaves begin as tiny, wet spots that progressively get larger and acquire dark brown cores surrounded by yellowish haloes. Severe infections may cause browning and drying of the affected leaf areas, as well as other substantial leaf damage that would reduce grain yield and photosynthetic efficiency. The illness spreads by raindrop splashes, irrigation water, and infected instruments. It grows best in warm, humid environments. In addition to the use of resistant rice types and the timely administration of bactericides, effective management options incorporate cultural practices including crop rotation and adequate drainage. In order to lessen brown spot's negative effects on rice production, research efforts are concentrated on figuring out the genetic basis of resistance and creating long-term disease management strategies.

2.2 Bacterial Leaf Blight

Bacterial leaf blight is a destructive plant disease caused by various bacterial pathogens, notably Xanthomonas oryzae pv. oryzae in rice and Xanthomonas campestris pv. campestris in cruciferous vegetables[1].

Fig.3. Bacterial Leaf Blight

This disease typically manifests as dark, water-soaked lesions on the leaves, eventually turning brown or black as the infection progresses. Bacterial leaf blight spreads rapidly under warm and humid conditions, making it a significant threat to crop production, especially in regions with favorable environmental conditions. Control measures for bacterial leaf blight often include planting disease-resistant varieties, practicing crop rotation, and applying copper-based bactericides. Additionally, cultural practices such as proper irrigation management and removal of infected plant debris can help minimize the spread of the disease. Early detection and prompt management are crucial for preventing widespread outbreaks and preserving crop yield and quality[4].

2.3 Leaf Blast

Leaf blast is a devastating fungal disease affecting rice crops, caused by the fungus Pyricularia oryzae.

Fig.4. Leaf Blast

This pathogen primarily targets the leaves of rice plants, leading to the formation of characteristic lesions that appear water-soaked and spindle-shaped in the early stages, eventually turning brown or gray as the disease progresses. Leaf blast can quickly spread under warm and humid conditions, posing a significant threat to rice production worldwide. Management strategies for leaf blast include planting resistant rice varieties, applying fungicides when necessary, and practicing cultural methods such as proper field drainage and crop rotation to reduce disease incidence. Early detection and integrated disease management approaches are essential for minimizing yield losses and preserving rice yields in affected regions[4].

2.4 Tungro

Tungro is a viral disease that affects rice crops, particularly in South and Southeast Asia, caused by a combination of two viruses: Rice tungro bacilliform virus (RTBV) and Rice tungro spherical virus (RTSV).

Fig.5. Tungro

The green leafhopper, Nephotettix virescens, is the disease's vector and can cause large yield losses in rice cultivars that are vulnerable. Reduced grain filling, yellowing or reddening of the leaves, and stunted growth are signs of tungro, which eventually lowers crop output. Using resistant rice types, reducing the green leafhopper population through pesticides or cultural methods, and encouraging integrated pest management techniques are the usual methods used to manage tungro.

3. Remedies for Each Disease

Brown Spot

Brown Spot, a significant threat to rice cultivation, demands a multifaceted approach for effective mitigation. Chemical methods, such as spraying Mancozeb (2.0g/lit) or Edifenphos (1ml/lit) 2 to 3 times at 10-15 day intervals, play a pivotal role in managing Brown Spot outbreaks. Botanical alternatives, including Neem Oil, Papaya Leaf Extract, and Aloe Vera Extract, exhibit efficacy in combating the disease. Furthermore, biological control methods like seed treatment with Pseudomonas fluorescens at 10g/kg of seed, followed by seedling dip, offer promising avenues for suppressing Brown Spot incidence.

Bacterial Leaf Blight

Leaf Blight, another formidable adversary of rice crops, demands strategic intervention to safeguard plant health. Chemical pesticides such as Nitrogen Fertilizers and Phosphorus Fertilizers prove indispensable in mitigating Leaf Blight's impact by bolstering plant resilience. Meanwhile, botanical remedies like Neem Oil, Ginger Extract, and Aloe Vera Extract offer natural alternatives for disease control. Biological agents such as Bacillus subtilis, Streptomyces spp., and Baculovirus exhibit promising outcomes in managing Leaf Blight outbreaks effectively.

Leaf Blast

Leaf Blast, a common affliction of rice plants, can be effectively managed through a range of remedies designed to combat its spread. Chemical methods involving Nitrogen Fertilizers and Phosphorus Fertilizers play a crucial role in controlling Leaf Blast progression by addressing nutrient deficiencies. Botanical alternatives like Neem Oil, Ginger Extract, and Aloe Vera Extract offer environmentally friendly options for containment. Furthermore, biological control agents such as Bacillus subtilis, Streptomyces spp., and Baculovirus demonstrate promising results in curtailing Leaf Blast outbreaks, providing a holistic approach to disease management in rice cultivation.

Tungro

Tungro, a persistent menace in rice cultivation, necessitates a comprehensive approach to containment. Chemical pesticides like Balanced NPK Fertilizers and Zinc Sulfate are pivotal in mitigating Tungro's spread by addressing nutrient imbalances. Botanical remedies such as Neem Oil, Garlic Extract, and Neem Cake (Neem Seed Kernel) present viable options for eco-friendly control measures. Furthermore, the application of biological agents such as Bacillus thuringiensis (Bt) and Trichoderma spp. showcases promising results in curbing Tungro infestations.

4. Methodology

From utilizing machine learning algorithms to employing deep learning models and integrating agricultural sensors and image data, the methodologies vary in complexity and innovation[11]. These approaches include dataset collection, preprocessing, feature extraction, and model training, demonstrating a diverse range of techniques to address the challenges of rice leaf disease detection. Additionally, ongoing research endeavors explore various methodologies for rice leaf disease detection, including the fusion of traditional image processing methods with state-of-the-art deep learning architectures. Concurrently, investigations delve into the utilization of drone imagery to automate disease detection processes. Each approach brings distinct perspectives to the table, collectively driving forward the frontier of rice disease management techniques, fostering innovation, and enhancing agricultural sustainability.

A. Block Diagram of Methodology

The block diagram illustrates the architecture of the Convolutional Neural Network (CNN) employed for rice leaf disease detection is as follows:

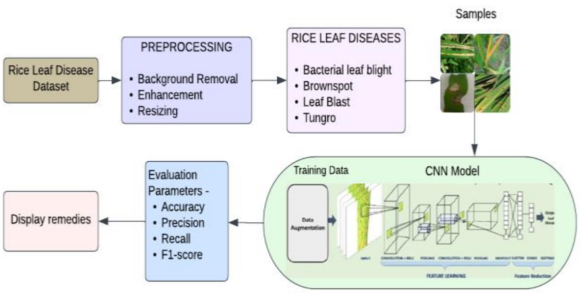

Fig.6. Block Diagram

4.1. Input Data Collection:

To create a reliable dataset, it's essential to collect a wide array of high-resolution images showcasing rice plants. These images should capture both healthy plants and those affected by common diseases like leaf blast, bacterial leaf blight, brown spot, and tungro. Each image needs detailed annotations, labeling it with the specific disease or indicating its healthy state. This meticulous process ensures the dataset's diversity and accuracy, facilitating effective training and evaluation of disease detection models [1].

The dataset, which started off with about 5932 samples, was obtained from Mendeley Data via Google for the research on rice disease identification using CNN. After extensive preprocessing, 5326 samples made up the final size of the dataset after it was improved. For consistency and interoperability, every sample in the collection is standardized to an image size of 256x256 pixels. A batch size of 32 was used during the training procedure to maximize memory consumption and computational efficiency. Because the model was trained over 20 epochs, it was able to learn everything and converge to the ideal values.

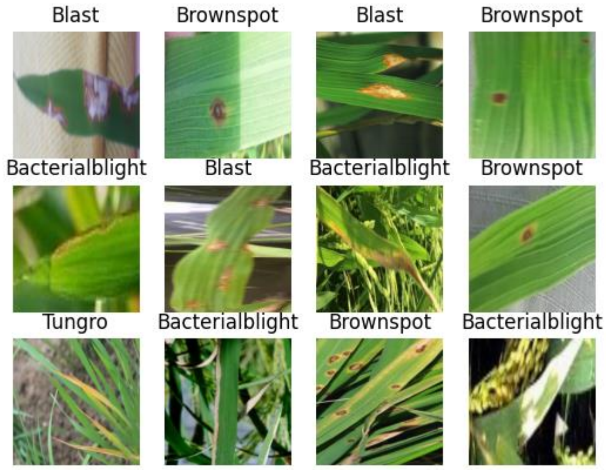

Fig.7. Input Data

4.2. Data Labeling and Data Splitting: Upon collection, the amassed data, sourced from online platforms, undergoes meticulous labeling to classify each image according to its disease type or health status. Subsequently, the dataset is partitioned into three distinct sections: Training, Testing, and Validation in the ratio of 80:10:10. This segmentation facilitates different training and testing ratios, ensuring the efficacy and generalization of the model.

4.3. Performance Evaluation:

In order to verify the model's robustness across a variety of datasets, the evaluation method carefully compares the predictions of the model with ground truth labels. We assess the model's capacity for generalization and its adaptability to different data distributions by altering the ratios between training and testing. We are able to obtain a full knowledge of the model's performance by analyzing Precision, Recall, F1-Score, and Accuracy in detail. This confirms the model's reliability in real-world agricultural settings[11][8][17].

The mathematical model listed below uses the terms TP (true positive), TN (true negative), FP (false positive), and FN (false negative).

yi: True label for the i-th data point, represented as an integer (index).

f(x)i: Predicted probability for the class corresponding to the true label (yi) by the model [6][11].

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \qquad \text{Eq. (1)}$$

$$\text{Recall} = \frac{TP}{TP+FN} \qquad \text{Eq. (2)}$$

$$\text{Precision} = \frac{TP}{TP+FP} \qquad \text{Eq. (3)}$$

$$\text{F1 Score} = \frac{2 * Precision * Recall}{Precision + Recall} \qquad \text{Eq. (4)}$$

$$\text{Loss} = -\,\text{sum}(yi * \log(f(x)i)) \qquad \text{Eq. (5)}$$

4.4. Disease Detection:

Utilizing the gathered evaluation parameters, disease detection is executed with superior accuracy compared to traditional methods. By analyzing the performance metrics derived from the evaluation process, the model's proficiency in identifying and classifying rice diseases is determined, ultimately advancing disease detection techniques in agriculture.

4.5. Remedies Suggestion:

Based on the disease detection results, tailored remedies are suggested. These remedies encompass a range of options, including botanicals, bio-pesticides, and chemical solutions, aimed at effectively combating and mitigating the identified rice plant diseases, thus promoting crop health and yield optimization.

B. Convolutional Neural Network

An extensive family of deep neural networks known as convolutional neural networks (CNNs) is utilized for a variety of applications utilizing structured grid data, including time-series data and speech recognition, in addition to image recognition and computer vision. Drawing inspiration from the visual cortex of the human brain, they are engineered to autonomously and adaptably assimilate spatial feature hierarchies from input images [6].

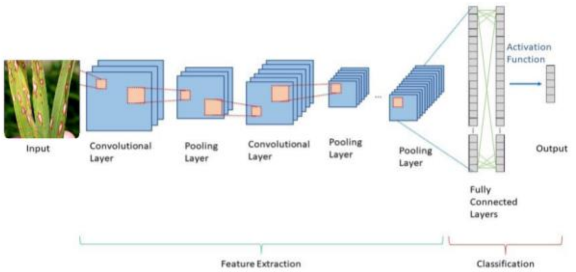

Fig. 8. Convolutional Neural Network Model

CNNs consist of several layers, each serving a specific purpose:

1. Input Layer: Raw input data, such as text sequences or images, is sent to the input layer. In picture tasks, the height, width, and number of color channels (e.g., red, green, and blue) of the input image match the dimensions of the input layer.

2. Convolutional Layer: The fundamental component of a CNN is the convolutional layer. Convolutional filters are used to the input data in order to identify particular characteristics or patterns. Feature maps are created by sliding each filter over the input and computing the dot product at each place. The existence of learnt features at various spatial places in the input is represented by these feature maps.

3. Pooling Layer: The most significant features are retained when the spatial dimensions of the input volume are downsampled using pooling layers. Two popular types of pooling operations are max pooling and average pooling, with max pooling being utilized more frequently. By lowering the number of parameters in the network and the computational complexity, pooling improves the efficiency of the model.

4. Activation Function: The network can approximate complex relationships in data by adding non-linearities through activation functions. Rectified Linear Unit, or ReLU, is one of the activation functions found in CNNs the most frequently. It adds non-linearity and makes it possible for the network to acquire more intricate representations of the data by substituting zero for negative values.

5. Fully Connected Layer: All of the neurons in one layer are connected to all of the neurons in the layer below through fully connected layers, also referred to as dense layers. Classification or regression tasks based on features learnt in previous layers are usually carried out by these layers at the conclusion of the network.

6. Output Layer: The network's ultimate output, which may be continuous values for regression tasks or class probabilities for classification tasks, is produced by the output layer. The output layer's activation function is determined by the type of task; softmax is frequently employed for multi-class classification tasks[13].

All things considered, CNNs have transformed computer vision by allowing machines to automatically extract characteristics from unprocessed input data. This has made CNNs incredibly effective tools for a variety of tasks, such as segmentation, object recognition, and image classification[1][7].

C. Software Used

The software used in the research on Convolutional Neural Networks (CNN) for rice disease diagnosis represents a thorough amalgamation of cutting-edge technologies and durable programming frameworks. The implementation makes use of key libraries such as Keras, TensorFlow, Matplotlib, Streamlit, NumPy, and Pandas, utilizing the flexibility and performance of Python. The CNN model is developed and trained using a combination of Keras and TensorFlow, which makes the process of building and optimizing complex neural network architectures easy. In order to improve interpretability and provide new insights, Matplotlib has become a crucial tool for visualizing data distributions, model performance indicators, and diagnostic charts. An interactive and user-friendly user interface is skillfully created using Streamlit, a new web application framework, enabling the model to be deployed and accessed with ease. Furthermore, NumPy and Pandas play a crucial role in preprocessing and data manipulation, guaranteeing compatibility and efficient data handling. In addition, Google Colab (version 3.8) is a cloud-based platform developed by Google, providing a web-based environment for writing and executing Python code.The development environment of Google Colab provides the processing power, scalability, and collaboration features necessary for training sophisticated deep learning models[6][11] .Additionally, a user-friendly website has been carefully designed to promote accessibility and dissemination of research findings. It offers a platform for exhibiting the created model, exchanging thoughts, and encouraging collaboration among the research community.

5. Results

The utilization of Convolutional Neural Network (CNN) models in agricultural research, specifically in rice disease detection, underscores the potential for advanced technology to revolutionize crop management practices. By achieving a remarkable 99% accuracy rate, the CNN model exemplifies its efficacy in accurately distinguishing between healthy and unhealthy rice plants. In-depth evaluation metrics such as precision, recall, and the F1 score provide nuanced insights into the model's performance, offering a comprehensive understanding of its capabilities in minimizing both false positives and false negatives. Implemented in Python programming with an 80:20 ratio for training and testing data, this study facilitates a thorough analysis of machine learning algorithms, paving the way for enhanced agricultural diagnostics and interventions.

Table 1.Classification Report

Disease Name	Accuracy	Precision	Recall	F1-Score
Bacterial Blight	0.97	0.99	0.96	0.97
Leaf Blast	0.96	0.96	0.99	0.98
Brown Spot	0.95	0.96	0.97	0.97
Tungro	0.98	1.00	0.98	0.99

The table highlights a remarkable **98%** overall accuracy, accompanied by precision, recall, and F1 score metrics for various rice plant diseases, showcasing the Convolutional Neural Network's (CNN) efficacy in disease identification[1][4].

5.1. Single Sample Prediction :

For a single image, the model displays the results, including labels indicating the actual disease, the predicted disease.

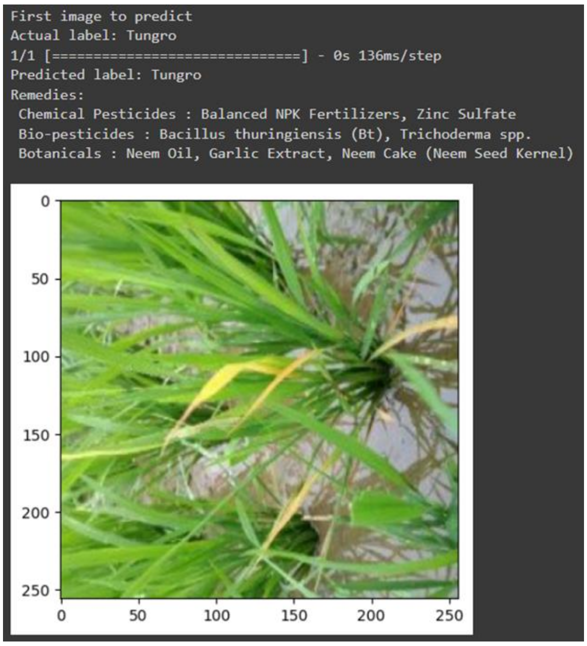

Fig. 9. Single Sample Prediction

The image depicts leaves exhibiting various diseases, with the model providing predictions that are highly accurate. Additionally, it quantifies its confidence level in the predicted results. This demonstrates the model's effectiveness in identifying and diagnosing leaf diseases, offering valuable insights for agricultural management and disease control.

These graphs provide insights into learning progress, overfitting identification, and model parameter optimization.

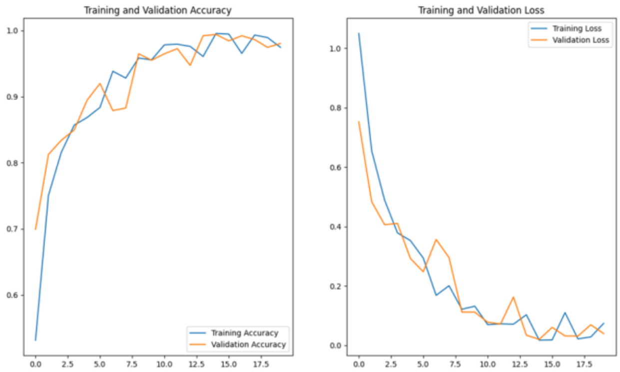

Fig.10. Training and Validation graph for accuracy and loss

The training accuracy serves as a benchmark for the model's proficiency in capturing patterns within the training dataset, reflecting its learning progress over successive epochs. Concurrently, tracking training loss provides insights into the model's optimization process, guiding adjustments to enhance performance. Validation accuracy acts as a litmus test for the model's adaptability to unseen data, crucial for real-world deployment scenarios. By monitoring validation loss, we can identify instances of overfitting and fine-tune the model to ensure robustness and reliability in practical applications. These metrics collectively form the foundation for assessing the model's efficacy in disease classification and its potential impact on agricultural sustainability.

Confusion matrix elucidates model classification performance by comparing predicted and actual labels, aiding in the assessment of accuracy, precision, recall, and F1 score.

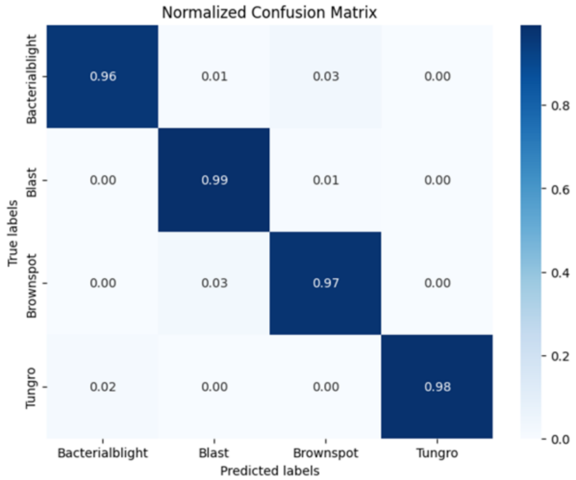

Fig.11. Confusion Matrix

In the context of the investigation into the identification and treatment of rice leaf disease The Convolutional Neural Network (CNN) model's effectiveness in categorizing various rice leaf illnesses is succinctly visualized through the use of a confusion matrix, which is made possible by Deep Learning. In a matrix structure, it arranges the predictions so that rows stand for the real rice leaf disease classes and columns for the classes that the CNN predicted. The deep learning techniques employed in this matrix facilitate the identification of instances of accurate and incorrect classifications, hence supporting the evaluation of the model's accuracy, precision, recall, and overall efficacy in the detection and management of rice leaf diseases.

5.2. Multiple Sample Prediction :

Moreover, the model's simultaneous analysis of nine images not only accelerates the assessment process but also ensures a thorough examination of the crop health status, leaving no room for oversight. Its ability to provide detailed insights such as the severity of the disease, potential spread patterns, and recommended treatments further empowers farmers with actionable intelligence to mitigate risks effectively. This holistic approach not only aids in immediate intervention strategies but also contributes to long-term disease management and prevention efforts. Additionally,

The model's adaptability allows for seamless integration into existing agricultural practices, fostering a synergistic relationship between cutting-edge technology and traditional farming methods for sustainable crop production.

Fig.12. Multiple Sample Prediction

Each disease is distinguished with precision, providing valuable insights for disease management and agricultural practices. The image output demonstrates the model's capability to detect specific diseases, facilitating timely interventions and remedies to safeguard rice crops.

5.3. Website Output:

Streamlit facilitates a website where users can upload images to diagnose rice diseases, receiving specific ailment predictions. The platform categorizes available remedies into three distinct types: biopesticides, botanical pesticides, and chemical pesticides. This classification system streamlines user access to agricultural solutions, empowering informed decision-making for disease management. By integrating image analysis and remedy categorization, the website enhances efficiency and comprehension in addressing rice cultivation challenges.

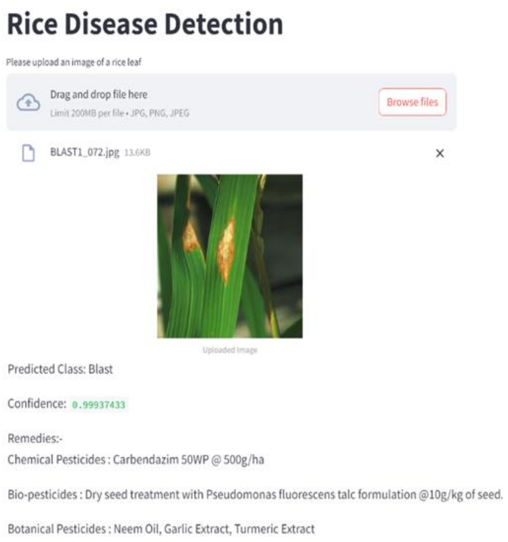

Fig.13. Website Output

The website utilizes a trained Deep Learning Convolutional Neural Network (CNN) to analyze input images of rice leaves and promptly identify the presence of blast, brown spot, tungro, or bacterial leaf blight. Upon image submission, users receive instant feedback on the detected disease type along with recommended remedies. This user-friendly interface streamlines the process of disease diagnosis and provides actionable insights for effective crop management.

6. Conclusion

Convolutional Neural Networks (CNNs) were utilized in this study to detect four important rice diseases: leaf blast, leaf blight, brown spot, and tungro. The study's conclusion is that the task was successfully completed. The model exhibited exceptional performance, achieving an astounding **98%** overall accuracy with low loss (0.0669), after undergoing a thorough evaluation process that employed metrics such as accuracy, precision, recall, and F1 score.

We also added further capability to the detection model by incorporating it into an easy-to-use web application that was created using Streamlit. Farmers can quickly diagnose sick rice leaves by uploading photos of the leaves to this portal. In addition, the app provides treatment recommendations that may be put into practice and are divided into three categories: botanicals, conventional fertilizers, and biopesticides. With the use of these insights, farmers are better equipped to manage the effects of crop diseases by making well-informed decisions.

By combining cutting-edge machine learning with intuitive web tools, the method enhances the identification of rice diseases and promotes sustainable agricultural practices. By helping farmers maintain crop health and maximize harvests, this integrated system improves rice cultivation's resilience and productivity.

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