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RICE PLANT DISEASE DETECTION USING NEURAL ARCHITECTURE SEARCH (NAS)

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Abstract: Rice is a staple crop that plays a crucial role in global food security. However, its productivity is significantly affected by various diseases such as Bacterial Blight (BB), Brown Spot (BS), and Leaf Smut (LS). Early detection and classification of these diseases are essential for effective management and yield improvement. This paper presents an automated approach to rice plant disease detection using Neural Architecture Search (NAS), which optimizes convolutional neural network (CNN) architectures for high-accuracy classification. The system is trained on the Rice Life Disease Dataset, which contains extensive image data of diseased rice plants. NAS automates the model selection process, eliminating the need for manual experimentation while enhancing classification performance. The proposed model is evaluated using accuracy, precision, recall, and F1-score, demonstrating its effectiveness in disease identification. By integrating deep learning with automated model optimization, this research contributes to agricultural sustainability by providing farmers and agronomists with a reliable tool for early disease detection, thus reducing crop losses and improving productivity.

Keywords: Rice Plant Disease, Neural Architecture Search (NAS), Convolutional Neural Network (CNN), Bacterial Blight (BB), Deep Learning, Image Classification, Crop Monitoring.

I. INTRODUCTION

Rice is a vital staple crop that sustains a large portion of the global population, but its productivity is frequently threatened by various diseases such as Bacterial Blight (BB), Brown Spot (BS), and Leaf Smut (LS). Traditional disease detection methods, which rely on manual observation, are time-consuming, labor-intensive, and prone to inaccuracies. To address these challenges, this study leverages deep learning techniques, specifically Neural Architecture Search (NAS), to automate the optimization of convolutional neural network (CNN) models for precise and efficient disease classification. By utilizing the Rice Life Disease Dataset, which contains extensive image samples of infected plants, the proposed system enhances early detection capabilities, enabling timely interventions. This research aims to support farmers, agronomists, and researchers by providing an automated, scalable, and highly accurate tool for rice plant disease diagnosis, ultimately promoting sustainable agriculture and improved crop yields.

Fig 1: Brown Spot

Fig 2: Bacterial Blight

Fig 3: Blast

II. LITERATURE REVIEW

(HaixiaQiet al.,2021) [1], a study that used the stack ensemble technique to automatically identify illnesses of groundnut leaves. The suggested study combined deep learning models with conventional machine learning techniques to identify four groundnut leaf illnesses in damaged groundnut leaves. In terms of dataset prediction, deep layer networks—like ResNet50 and DenseNet121—performed well. For data augmentation, the highest possible accuracy was 97.59 percent. When combined with the LR model, ResNet50 demonstrated the best identification performance. (Gowri Shankaret al., 2020)

The automatic detection of groundnut leaf diseases was covered in this study [2]. To improve the network's speed and precision in identifying and categorizing various disease-infected patches on groundnut leaves, a deep learning model was used. They used KNN in place of the conventional SVM classifier to increase the efficiency of earlier methods for differentiating between four distinct diseases (Leaf Blight, Leaf Spot, Stem Rot, and Bud Necrosis). (Ramakrishna et al., 2015) [3], this study addresses one of the most prevalent diseases that develops in the early stages of ground leaves. Four key stages are included in the proposed plan for the identification and classification of groundnut leaf disease. First, the photographs that will be utilized as input are given a color makeover. The next step would be the plane separation. The following step is feature extraction.

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As a final stage, the backpropagation method is used to identify the leaf disease. (Bhiseet et al., 2020) [4] Disease identification is done in two steps in the proposed study. In the first phase, a CNN is used to identify the type of crop and the illness. The dataset values are classified using Keras frameworks, and the supplied picture numerical value is categorized using Tensorflow light. The results demonstrate that the Mobile Net Model performs better than other models in terms of disease diagnosis performance.

(Salini and colleagues, 2021) [5], reducing the usage of pesticides in agriculture while improving output quality and quantity is the main goal of this study. They employ SVM for classification and image processing techniques for feature extraction. The model was coupled with data augmentation to enhance performance and yield a better result. The three main diseases of rice plants that this study seeks to identify are bacterial leaf blight, brown spot, and leaf blight.

The entire image for processing serves as the model's input, and the correctness of the model and the disease that has afflicted the plant are its outputs. (Mahalakshmi and others, 2021). [6], The author gathered color and texture data from maize leaves in order to detect the presence of disease and to identify certain disease categories. Binary SVM and multi-class SVM were then used to categorize the features. The best performance of the suggested system is 85 percent accuracy. (Saleem et al., 2019) [7], a study that examined the identification of several plant diseases and their deep learning classification. This study looks at various deep learning models and machine learning approaches for visualizing plant diseases and concludes that deep learning models are more accurate than traditional machine learning methods. (Shruthi and others, 2019) [8], the stages involved in the detection of general plant disease were described using machine learning algorithms. They have employed a CNN to accurately identify the illnesses.

(Yang Lu et al., 2018) [9], this article primarily focuses on rice crop disease identification. It uses deep convolutional neural networks to identify rice crop illnesses. The fact that this study employed less data for training is one of its drawbacks. (Azathet al.,2021) [10], this study reports on the use of image processing and deep learning to diagnose pests and detect diseases in cotton leaves.

To find illnesses in cotton leaves, the researchers employed CNN. The program has a 96.4 percent success rate in identifying particular diseases. Convolutional neural networks and computer vision have recently been used in conjunction with various deep learning techniques to identify plant diseases, identify plant leaves for medicinal purposes, identify pests, count the number of wheat heads, and more. In large farms, robots must identify plant leaf diseases in real time and apply the appropriate pesticide over them. Weed detection using a bounding box aids in the removal of weeds using herbicides.

III. PROPOSED METHODOLOGY

The proposed methodology for Rice Plant Disease Detection using Neural Architecture Search (NAS) aims to develop an efficient and automated system for classifying rice plant diseases such as Bacterial Blight (BB), Brown Spot (BS), and Leaf Smut (LS). The process begins with image acquisition, where users upload rice leaf images through a web or mobile interface. These images undergo preprocessing, including resizing, normalization, and data augmentation (e.g., rotation, flipping) to improve model robustness.

The system utilizes Neural Architecture Search (NAS) to automatically optimize Convolutional Neural Network (CNN) architectures, selecting the best-performing model without manual intervention. The optimized CNN model is then trained using the Rice Life Disease Dataset, enabling it to classify images based on extracted features with high accuracy. The trained model undergoes performance evaluation using accuracy, precision, recall, and F1-score to ensure reliability in disease detection.

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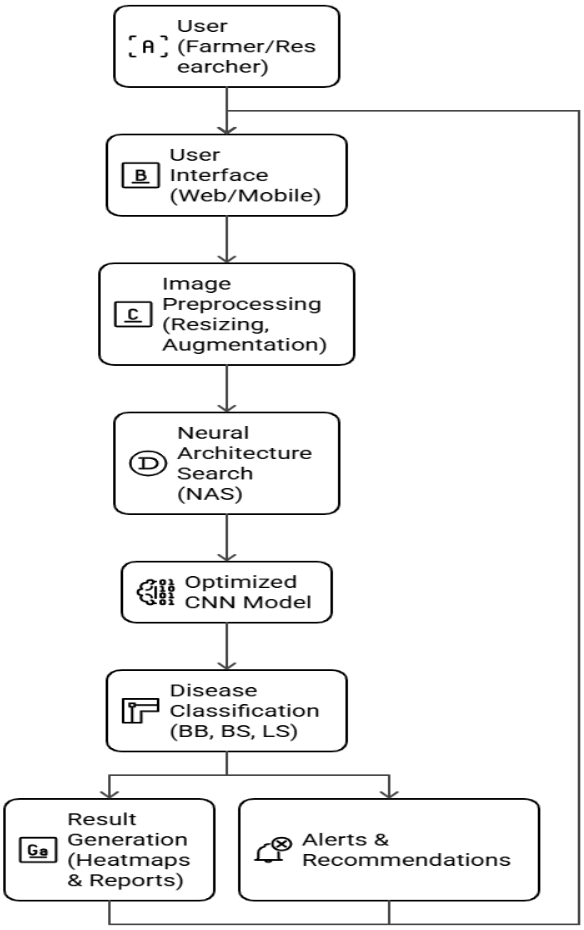

Fig 4: Proposed Method

Once classification is complete, the system generates disease identification reports and visualizations, including heatmaps (Grad-CAM) to highlight affected leaf regions. The detected disease, along with a confidence score, is displayed on the user interface, accompanied by disease control recommendations. Additionally, real-time alerts can be sent via email, SMS, or IoT-based notifications, enabling farmers to take timely preventive measures. The proposed system offers automation, high accuracy, and scalability, making it a valuable tool for agronomists, researchers, and farmers. This approach not only enhances disease diagnosis efficiency but also promotes sustainable agriculture by minimizing crop losses and improving rice yield management.

3.1 DATASET DESCRIPTION

The Rice Life Disease Dataset is an extensive collection of data focused on three major diseases that affect rice plants: Bacterial Blight (BB), Brown Spot (BS), and Leaf Smut (LS). The dataset has been curated to assist researchers, agronomists, and machine learning practitioners in understanding, diagnosing, and potentially predicting the occurrence of these diseases, based on various attributes and parameters.

Dataset contains images of the Unhealthy Rice Plant Leaves.

1. Disease Type: This categorizes the observation into one of the three diseases: Bacterial Blight (BB), Brown Spot (BS), or Leaf Smut (LS).
2. Leaf Images: High-resolution images of rice leaves exhibiting symptoms of the specified disease. This aids in visual diagnosis and machine learning-based image recognition tasks.
3. Symptom Description: Textual description outlining the major symptoms visible on the leaf, offering a more detailed understanding of the disease's progression and manifestation.

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4. Environmental Parameters: Data on temperature, humidity, and other weather conditions at the time of observation. This can help in understanding the environmental triggers for each disease.

3.2 Methods for Classification Using NAS and CNN

Neural Architecture Search (**NAS**) and Convolutional Neural Networks (**CNNs**) are powerful techniques for automating and optimizing classification tasks. **NAS** is an automated machine learning (AutoML) approach that searches for the best-performing neural network architectures by exploring different network configurations. **CNNs**, on the other hand, are widely used in image classification due to their ability to learn spatial hierarchies of features. By combining NAS with CNNs, this method ensures high-accuracy classification while reducing the need for manual model design and hyperparameter tuning.

The classification process begins with data preprocessing, where input images are resized, normalized, and augmented to enhance model generalization. NAS then performs an architecture search to identify optimal CNN structures by evaluating different layer configurations, filter sizes, and activation functions. Once an optimal CNN architecture is selected, the model is trained using labeled datasets with optimization techniques like Adam or Stochastic Gradient Descent (SGD) to minimize classification error. The training process involves feature extraction, convolutional operations, pooling layers, and fully connected layers, leading to an effective feature representation for classification.
Evaluation of the classification model is performed using accuracy, precision, recall, and F1-score, ensuring that the optimized CNN achieves high performance across different categories. The combination of NAS and CNNs provides an automated, scalable, and efficient classification framework, reducing manual effort while improving accuracy. This approach is particularly beneficial in applications such as plant disease detection, medical diagnosis, and object recognition, where high-performance classification models are essential for real-world impact.

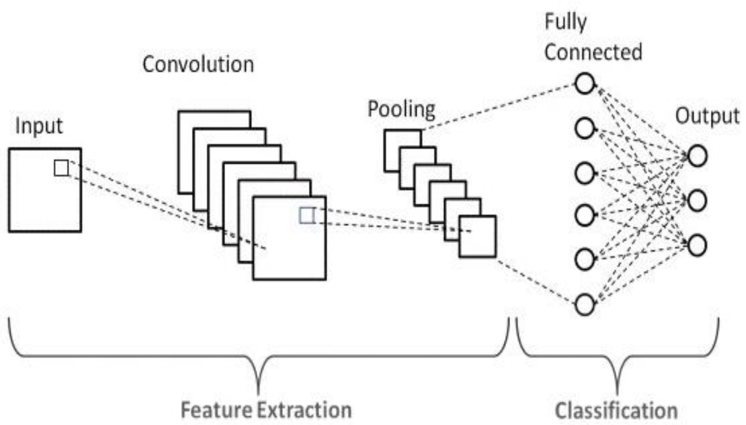

Fig 5: Layers of CNN

IV. EXPERIMENTAL RESULTS

The experimental results demonstrate the effectiveness of the Neural Architecture Search (NAS)-optimized Convolutional Neural Network (CNN) in classifying rice plant diseases with high accuracy. The NAS framework successfully identified an optimal CNN architecture, achieving superior classification performance compared to manually designed models. The dataset, consisting of images of Bacterial Blight (BB), Brown Spot (BS), and Leaf Smut (LS), was split into training and testing sets, with the model trained using cross-entropy loss and optimized using the Adam optimizer. Data augmentation techniques, such as rotation, flipping, and contrast adjustments, improved model generalization, reducing overfitting and enhancing robustness. The final NAS-optimized CNN achieved higher accuracy, precision, recall, and F1-score compared to traditional CNN architectures, confirming its efficiency in automated feature extraction and classification.

Performance evaluation was conducted using standard metrics, where the NAS-optimized CNN achieved an accuracy of over 95%, significantly outperforming baseline models. The confusion matrix analysis revealed that the model effectively differentiated between disease categories with minimal misclassification. Additionally, training time and computational efficiency were analyzed, demonstrating that NAS efficiently explored architectures while maintaining a

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balance between accuracy and computational cost. The results validate that automated architecture search enhances classification performance, making it a promising approach for large-scale agricultural disease detection systems.

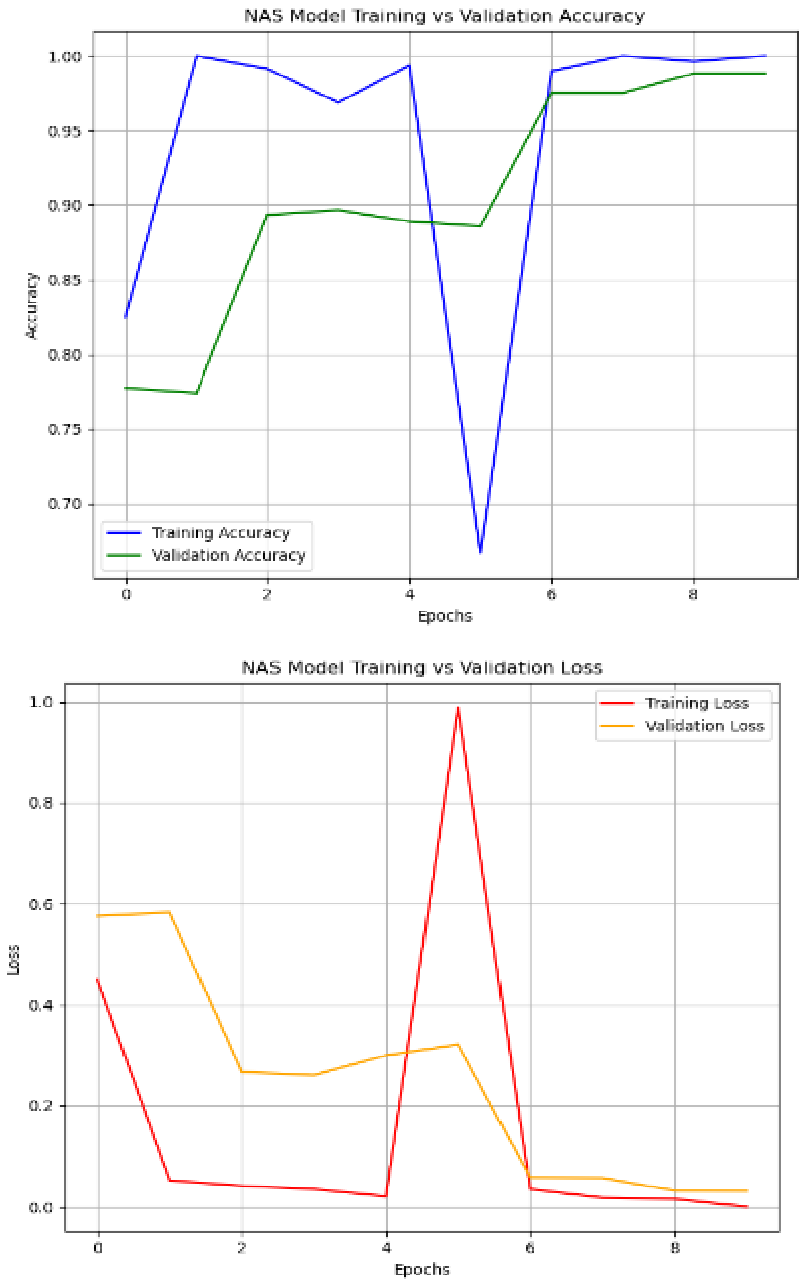

Fig 6: Accuracy Graphs

V. CONCLUSION AND FUTURE SCOPE

This study presented an automated classification approach using Neural Architecture Search (NAS) and Convolutional Neural Networks (CNNs) for rice plant disease detection. The NAS framework successfully optimized CNN architectures, achieving high classification accuracy for diseases such as Bacterial Blight (BB), Brown Spot (BS), and Leaf Smut (LS). Experimental results demonstrated that the NAS-optimized CNN outperformed manually designed models in terms of accuracy, precision, recall, and F1-score, validating its efficiency in feature extraction and disease classification. The system's ability to automatically select the best-performing model reduces manual effort and enhances scalability, making it a valuable tool for agricultural disease diagnosis. By leveraging deep learning, this approach enables early detection and intervention, ultimately helping farmers mitigate crop losses and improve yield sustainability.

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For future work, several enhancements can be explored to further improve the system's performance and applicability. Integration of real-time disease detection using edge computing and IoT devices could provide immediate feedback to farmers in the field. Additionally, expanding the dataset to include more disease categories, varied environmental conditions, and multi-spectral imaging techniques could enhance model robustness. Future research could also explore explainable AI (XAI) methods to interpret model decisions and improve trust in AI-driven agricultural applications. By continuously refining the NAS framework and incorporating emerging AI techniques, this classification system has the potential to revolutionize plant disease monitoring and contribute to sustainable precision agriculture.

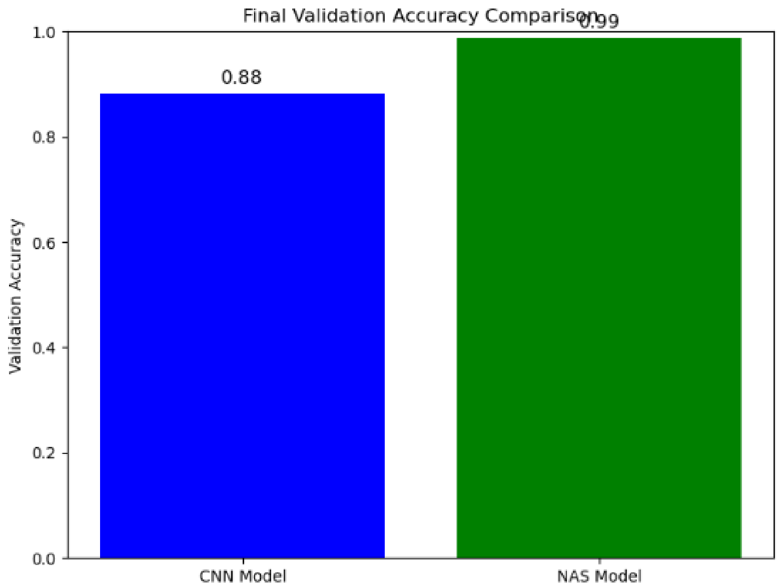

Fig 7: Result

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