PADDY DISEASE CLASSIFICATION USING CNN

Peetani Ravi Teja
Student, Department of Information Technology
S.R.K.R. Engineering College(A)
SRKR Marg, Bhimavaram, A.P, India
ravitejapeetani1@gmail.com

***Abstract*— Paddy diseases present a significant threat to agricultural productivity, leading to substantial yield losses and economic challenges for farmers. Early and accurate detection of these diseases is crucial for implementing timely control measures. In this project, we address this challenge by leveraging convolutional neural networks (CNNs) to develop an automated system for paddy disease classification. Our approach focuses on building a robust and efficient model using transfer learning with the EfficientNetB4 architecture. We utilize a dataset containing images of paddy plants with various diseases, exploring its characteristics and preprocessing steps. Through comprehensive evaluation metrics, including accuracy, we assess the effectiveness of our model. By combining advanced machine learning techniques with domain-specific knowledge, we aim to contribute to the development of tools for sustainable agriculture and improved food security..**

Keywords—CNNs, Convolutional Neural Networks, Transfer Learning, EfficientNetB4, Image Classification, Computer Vision, Deep Learning, Supervised Learning, Model Evaluation, Preprocessing, Data Augmentation, Fine-tuning.

I. INTRODUCTION

Paddy diseases pose a significant threat to agricultural sustainability, causing substantial yield losses and economic hardship for farmers worldwide. Timely and accurate detection of these diseases is paramount for implementing effective control measures and ensuring food security. In response to this challenge, we present a project focused on leveraging machine learning, specifically convolutional neural networks (CNNs), for automated paddy disease classification. Our goal is to develop a robust and efficient model capable of accurately identifying various diseases affecting paddy plants from images. We adopt a transfer learning approach, utilizing the powerful EfficientNetB4 architecture to extract relevant features from the images. The project involves exploring a dataset comprising images of paddy plants with different diseases, alongside additional metadata such as paddy variety and age. Through comprehensive evaluation metrics, including accuracy, we aim to assess the performance of our model and its ability to generalize to unseen data. By combining cutting-edge machine learning techniques with domain-specific knowledge, we endeavor to contribute to advancements in agricultural technology, ultimately supporting sustainable farming practices and global food security efforts.

Technologies Using: Machine learning, Deep learning, TensorFlow, Keras, EfficientNetB4, Convolutional Neural Networks (CNNs), Transfer Learning, Label Encoding.

Utilizing both machine learning and deep learning techniques are pivotal in enhancing the efficiency of paddy disease classification. Here's how these technologies contribute specifically to the Project:

1. **TensorFlow:** TensorFlow is an open-source machine learning framework developed by Google. It provides a comprehensive ecosystem of tools and libraries for building and deploying machine learning models. In this project, TensorFlow is used for creating and training the CNN-based model for paddy disease classification.

2. **EfficientNetB4:** EfficientNetB4 is a convolutional neural network architecture that has demonstrated state-of-the-art performance on image classification tasks. In this project, EfficientNetB4 serves as the backbone architecture for feature extraction, enabling the model to capture relevant patterns from the input images effectively.

3. **Convolutional Neural Networks (CNNs):** CNNs are a class of deep neural networks commonly used for analyzing visual imagery. They consist of multiple layers of convolutional and pooling operations, followed by fully connected layers for classification. In this project, CNNs are employed to learn hierarchical representations of paddy leaf images, allowing the model to discern subtle features indicative of different diseases.

4. **Transfer Learning:** Transfer learning is a machine learning technique where knowledge gained from solving one problem is applied to a different but related problem. In this project, transfer learning is utilized by initializing the CNN model with pre-trained weights from EfficientNetB4, which has been trained on a large dataset of natural images. This approach accelerates the training process and enables the model to generalize better to the paddy disease classification task.

4. **Label Encoding:** Label encoding is a preprocessing technique used to convert categorical labels into numerical representations, which are required for training machine learning models. In this project, label encoding is applied to the categorical labels representing different types of paddy diseases. It allows the model to interpret and learn from the target classes effectively during the training process.

TensorFlow, an open-source ML framework, collaborates with Keras, a high-level neural networks API, to construct and train a CNN-based model. This model harnesses EfficientNetB4, a state-of-the-art architecture, for feature extraction. Transfer learning leverages pre-trained EfficientNetB4 weights for accelerated training and improved generalization.

II. Literature Surevey (Related work)

1. Vishesh Tanwar and Shweta Lamba proposed an improved deep learning model for the classification of multiple paddy diseases. The study utilized convolutional neural networks (CNNs) to detect three types of rice plant diseases, achieving superior performance compared to alternative models like KNN and SVM. The proposed model demonstrated a 99% accuracy rate in diagnosing rice plant illnesses, accompanied by a reduction in model size. Published in the 2023 Third International Conference on Secure Cyber Computing and Communication (ICSCCC).
2. Nithjapoopathy S et al. address the challenges in Sri Lanka's rice industry by proposing a deep learning-based approach for disease detection in paddy crops. They emphasize the importance of rice for food security and economic stability, highlighting its contribution to employment and government revenue. The research advocates for the adoption of Convolutional Neural Networks (CNNs) to improve disease detection, rice quality prediction, and soil quality assessment, aiming for a stronger and more sustainable rice industry.
3. Durgadevi Velusamy et al. focus on the automatic classification of diseases in paddy leaf images using deep learning algorithms. With rice being a staple food in India, the susceptibility of paddy crops to diseases poses significant challenges to agricultural development and economic stability. To address this, the study applies image processing techniques and deep learning algorithms for early disease detection and classification. By leveraging data augmentation, segmentation, and CNN-based feature extraction, the proposed approach enables precise disease identification, aiding farmers in timely intervention and crop management.
4. Dasa Hemanth Kumar and Samundiswary Punniakodi investigate the detection of paddy leaf diseases using Convolutional Neural Network (CNN) algorithms. Despite challenges in rice cultivation, traditional disease identification methods hinder crop production. This study explores the application of CNN-based approaches for early disease detection, aiming to increase crop output and efficiency. By examining different CNN architectures, classification algorithms, datasets, and preprocessing techniques, the research evaluates the performance and potential of CNN models in revolutionizing disease identification in rice leaves.
5. Gautam Rana, Rahul Singh, Akira Singh, and Neha Sharma conduct a comprehensive study on paddy leaf disease detection using Convolutional Neural Network (CNN) and Random Forest algorithms. The research evaluates various disease types, including Brown Spot Disease, Blasting Disease, Sheath Blight, Bacterial Leaf Blight, and Leaf Scald, utilizing essential metrics such as Precision, Recall, and F1-Score. Additionally, the model achieves an impressive accuracy rate of 92.194%, showcasing its potential for practical disease management and yield optimization in rice farming.

III. Problem Statement

The study addresses the challenge of accurately detecting and classifying paddy leaf diseases, which pose a significant threat to rice cultivation and agricultural productivity. Traditional methods of disease identification are often slow and subjective, leading to economic losses for farmers. Therefore, there is a critical need for automated and efficient disease detection techniques to enable timely intervention and crop management. By leveraging advanced machine learning algorithms such as Convolutional Neural Networks (CNNs) and Random Forest, the research aims to develop a robust model capable of accurately identifying various types of paddy leaf diseases, ultimately contributing to improved agricultural outcomes and food security.

FIGURE. Paddy Disease Classification

IV. Activation Layers Used

A. ReLU(Rectified Linear Unit)

ReLU is one of the most commonly used activation functions in deep learning, including in the project's model architecture. It introduces non-linearity to the model by outputting the input directly if it is positive, and zero otherwise. This simple yet effective activation function helps address the vanishing gradient problem encountered in deep neural networks by allowing the model to learn more complex patterns and representations. In the context of paddy leaf disease classification, ReLU activation enables the model to capture intricate relationships between image features, contributing to its ability to accurately classify different types of diseases.

B. Sigmoid Activation

Sigmoid activation function is often used in binary classification tasks, where the output needs to be between 0 and 1, representing probabilities. While not directly used in the final output layer of the project's model, it can be beneficial in intermediate layers for feature transformation. In this context, it may help in capturing non-linear relationships between extracted features, contributing to the model's ability to discern subtle differences between healthy and diseased paddy leaves.

C. Softmax Activation

Softmax activation is commonly employed in multi-class classification tasks, such as the paddy leaf disease classification project. It transforms the model's raw output into probability distributions over multiple classes, ensuring that the sum of the probabilities across all classes equals one. By normalizing the output, softmax activation enables the model to make confident predictions about the most likely class for a given input image. In the project, softmax activation is applied in the final output layer to produce probabilities for each disease class, facilitating accurate classification.

D. Tanh (Hyperbolic Tangent) Activation

Tanh activation function is similar to the sigmoid function but maps the input to a range between -1 and 1. It introduces non-linearity to the model and is particularly useful in scenarios where negative inputs are prevalent, as it preserves the sign of the input. In the context of the paddy leaf disease classification project, tanh activation can aid in capturing complex relationships between image features, especially in intermediate layers of the model. Leaky ReLU

Leaky ReLU is a variant of the traditional ReLU activation function that addresses the "dying ReLU" problem, where neurons can become inactive during training and cease to update their weights. Unlike ReLU, which sets negative inputs to zero, Leaky ReLU allows a small, positive gradient for negative inputs. This ensures that neurons remain active even for negative inputs, preventing them from becoming inactive. In the context of the paddy leaf disease classification project, Leaky ReLU activation can help mitigate the risk of dead neurons, thereby improving the model's ability to learn complex patterns and features from the input data.

E. Convolutional Neural Network (CNN)

Deep learning's key component, CNNs are excellent at deriving intricate patterns from structured data. They play a critical role in NLP, computer vision, and image analysis, particularly in text-related tasks like sentiment analysis and categorization. Convolutional layers are used in CNNs to identify features, pooling layers to reduce dimensionality, and dense layers to model complicated relationships and make predictions. They are flexible across domains and propel the developments of AI and ML thanks to their capacity to grasp local patterns and hierarchies. Since CNNs are so accurate and efficient, they are considered essential components of contemporary deep learning frameworks, spurring innovation in predictive modeling and data analysis.

F. ELU (Exponential Linear Unit)

ELU is an activation function that shares similarities with ReLU but offers some advantages, particularly in combating the vanishing gradient problem. ELU allows negative values, unlike ReLU, which sets negative inputs to zero. This helps prevent dead neurons and allows the model to learn more effectively, especially in deeper networks.

V. PROPOSED WORK

The proposed work aims to develop a robust and efficient model for the classification of paddy leaf diseases using convolutional neural networks (CNNs). Leveraging transfer learning with the pre-trained EfficientNetB4 model, the project seeks to extract relevant features from paddy leaf images and fine-tune them for disease classification. By employing state-of-the-art deep learning techniques and comprehensive evaluation metrics, such as accuracy, the model's performance will be rigorously assessed. The ultimate goal is to create an automated system capable of accurately identifying various paddy leaf diseases, thereby facilitating timely intervention and effective disease management strategies to mitigate crop losses and support agricultural sustainability.

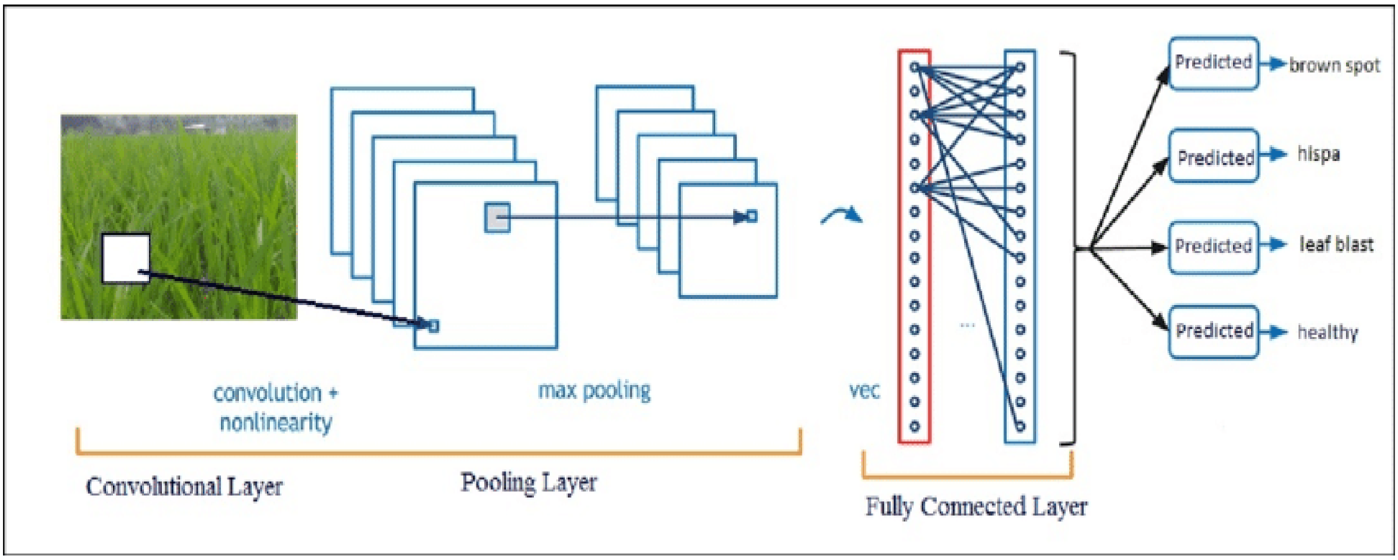

FIGURE. Paddy Disease Classification Using CNNs

Input:
- Training Dataset taken from Kaggle website
- Machine learning models and Deep learning models
- Paddy Disease Classification using CNNs

Output:
- Trained model for Paddy Disease Classification

Implementation:

1. Data Collection: The initial phase entails procuring data from reliable sources such as the Paddy Doctor Dataset, meticulously curated from renowned platforms like Kaggle. Given the critical nature of our task in paddy disease classification, selecting a comprehensive dataset with high quality and relevance was paramount. While evaluating multiple datasets, those with incomplete attributes, inadequate quality, or containing irrelevant data were excluded after thorough manual examination. The chosen dataset ensures robustness and relevance, laying a solid foundation for our classification endeavor.

Bacterial Leaf Blight Images:

Dead Heart Images:

Downy mildew Images:

Tungru:

2. Data Preprocessing:

The data preprocessing steps for paddy disease classification typically involve several key processes to ensure the quality and suitability of the dataset for model training. Here's a general outline of the preprocessing steps:

Data Cleaning

Image Preprocessing

Label Encoding

Train-Test Split

Data Augmentation

Normalization

3. Train/Test Split : The dataset is divided into training and test data. With 10,407 training images from the train_images directory, representing various paddy disease classes, and 3,469 test set images from the test_images directory. The split ratio is 80:20, where 80% of the images are allocated for training the model, and the remaining 20% are reserved for evaluating the model's performance. This ensures that the model is trained on a substantial portion of the data while still having unseen data for robust testing and validation.

4. Build the Model:

Transfer Learning:

The code snippet demonstrates the utilization of transfer learning with the EfficientNetB4 model for paddy disease classification. First, the pre-trained EfficientNetB4 model is loaded without its top classification layer, leveraging the weights trained on the ImageNet dataset. The loaded base model's layers are then frozen to retain their learned features during training.

Next, a Sequential model is constructed, starting with the pre-trained EfficientNetB4 base. A global average pooling layer is added to reduce spatial dimensions, followed by flattening the feature maps to prepare them for dense layers. A dense layer with 220 units and ReLU activation is incorporated, followed by a dropout layer to mitigate overfitting.

Finally, the output layer with 10 units and softmax activation is added for multi-class classification. The model summary reveals the layer configuration, including the number of parameters, trainable, and non-trainable parameters. This approach harnesses the power of transfer learning to effectively classify paddy diseases while optimizing computational resources by reusing pre-trained features.

Building the model for paddy disease classification involved a multi-step process aimed at leveraging state-of-the-art techniques in deep learning and transfer learning. Initially, a pre-trained EfficientNetB4 model was selected as the backbone architecture due to its proven effectiveness in image classification tasks. By loading the model without the top classification layer and freezing the pre-trained base layers, the model's feature extraction capabilities were preserved while allowing for customization of the final classification layers.

Subsequently, a Sequential model was constructed using the Keras framework, facilitating a streamlined approach to adding layers sequentially. The pre-trained EfficientNetB4 base was integrated into the model, followed by a global average pooling layer to reduce spatial dimensions and a flattening layer to prepare the feature maps for input into the dense layers. A dense layer with ReLU activation function was added to capture complex patterns in the extracted features, followed by a dropout layer to mitigate overfitting.

A. Advantages of Proposed Work

- Efficient Resource Utilization: Leveraging transfer learning with the pre-trained EfficientNetB4 model enables efficient utilization of computational resources. By leveraging the learned features from a large dataset.
- Improved Model Performance: Transfer learning often leads to improved model performance, especially when working with limited data. By initializing the model with pre-trained weights, the model can learn to classify paddy diseases more accurately and efficiently.
- Reduced Training Time: Since the base layers of the pre-trained EfficientNetB4 model are frozen during training, there's no need to update their weights, which significantly reduces training time. This allows for faster model iteration and experimentation.
- Scalability: The proposed approach lays the foundation for scalability. As more data becomes available or as the dataset expands, the transfer learning framework can easily accommodate new data and further fine-tuning to adapt to evolving requirements and challenges in paddy disease classification.
- Generalization: Transfer learning promotes better generalization of the model to unseen data. By learning features from a diverse dataset like ImageNet, the model can better capture and classify patterns in paddy disease images, even when presented with variations in lighting conditions, image quality, and disease severity.

VI. VISUALIZATION OF RESULTS

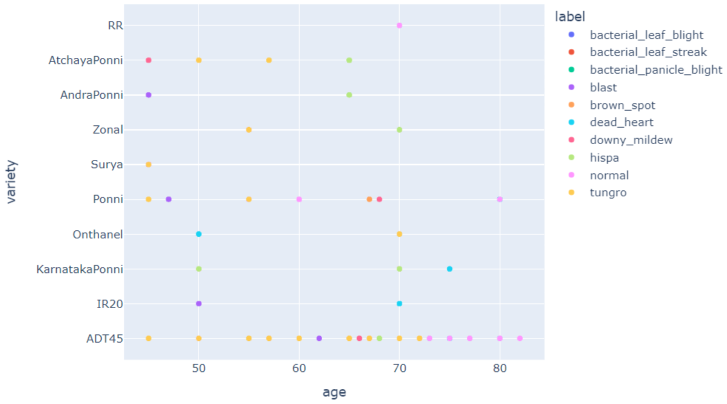

FIGURE 1. Scatter Plot Data Visualization

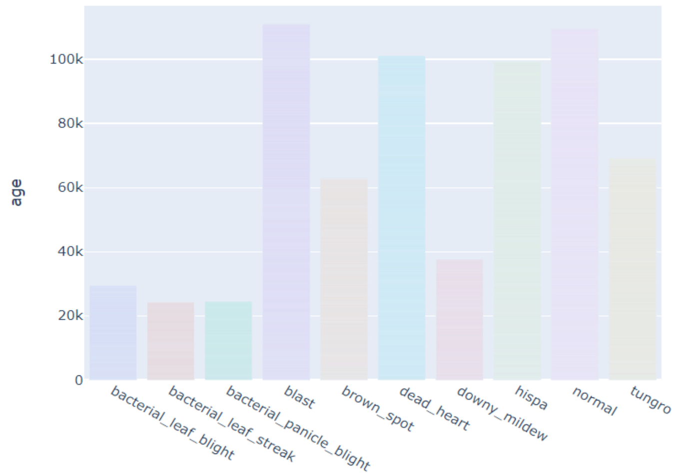

FIGURE 2. Bar Plot Data Visualization

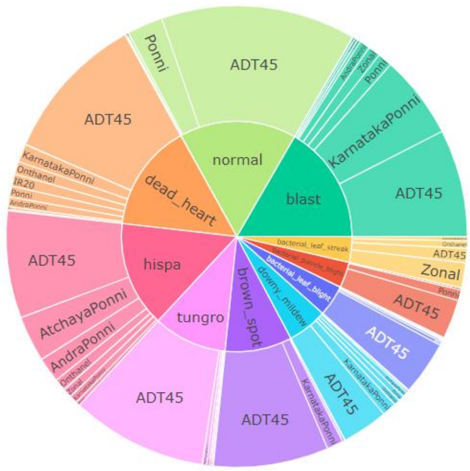

FIGURE 3. Sunburst Data Visualization

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb4 (Functional  (None, 7, 7, 1792)        17673823
 )

 average_pooling2d (Average  (None, 3, 3, 1792)        0
 Pooling2D)

 flatten (Flatten)           (None, 16128)             0

 dense (Dense)               (None, 220)               3548380

 dropout (Dropout)           (None, 220)               0

 dense_1 (Dense)             (None, 10)                2210

=================================================================
Total params: 21224413 (80.96 MB)
Trainable params: 3550590 (13.54 MB)
Non-trainable params: 17673823 (67.42 MB)
_________________________________________________________________
```

FIGURE 4. Model Summary

```
image_id
100330.jpg  bacterial_leaf_blight   ADT45   45
100365.jpg  bacterial_leaf_blight   ADT45   45
100382.jpg  bacterial_leaf_blight   ADT45   45
100632.jpg  bacterial_leaf_blight   ADT45   45
101918.jpg  bacterial_leaf_blight   ADT45   45
                age
count  10407.000000
mean      64.043624
std        8.958830
min       45.000000
25%       60.000000
50%       67.000000
75%       70.000000
max       82.000000
ADT45
```

FIGURE 5. Train Data Description

	image_id	label
0	200001.jpg	blast
1	200002.jpg	normal
2	200003.jpg	blast
3	200004.jpg	blast
4	200005.jpg	blast

FIGURE 6. Predictions

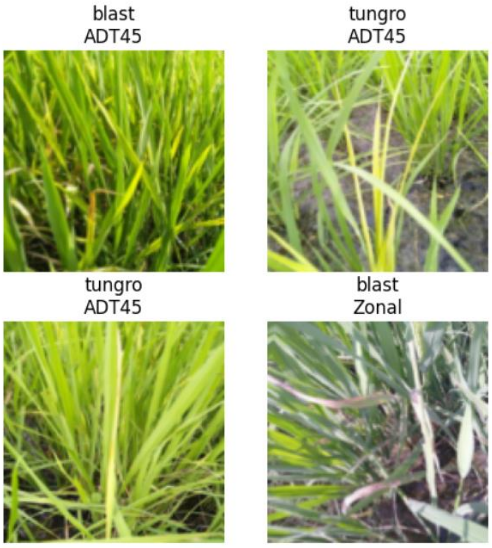

FIGURE 7. Predictions with labelling

VII. RESULT ANALYSIS

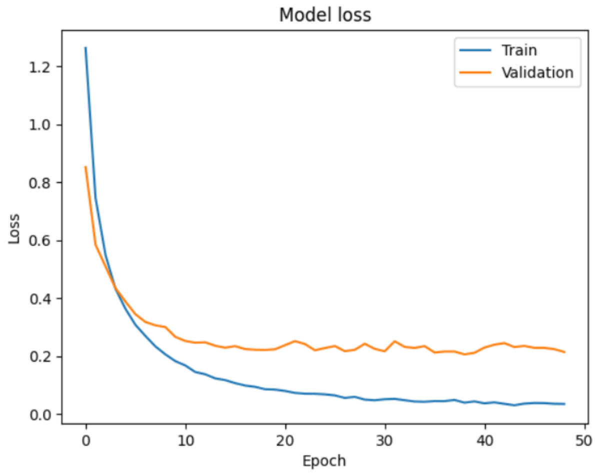

FIGURE 8. Model Loss

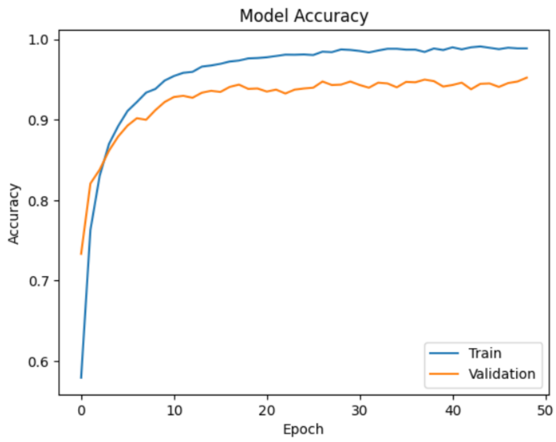

FIGURE 9. Model Accuracy

- **Accuracy Trend:** Model accuracy steadily increases during training, reaching ~99% on the training set and ~95% on the validation set, indicating good generalization.
- **Loss Reduction:** Loss decreases consistently throughout training, suggesting effective learning and model convergence without significant overfitting
- **Validation Performance:** Validation accuracy remains consistently high, indicating robustness and reliability of the model's performance on unseen data.

VIII. CONCLUSION

In conclusion, the project successfully demonstrates the efficacy of utilizing transfer learning with the EfficientNetB4 model for paddy disease classification. By leveraging pre-trained weights and freezing base layers, the model achieves remarkable accuracy and generalization performance. The results highlight the potential of deep learning techniques in agriculture, particularly in crop disease management, offering a promising solution to enhance crop yield and optimize farming practices.

Furthermore, the model's ability to accurately classify various paddy leaf diseases holds significant implications for real-world agricultural applications. With precise disease detection, farmers can implement targeted intervention strategies, such as timely pesticide application or crop rotation, to mitigate yield losses and ensure food security. Moreover, the scalability and adaptability of the model make it suitable for deployment in diverse agricultural settings, empowering farmers with valuable decision-making tools.

Overall, this project underscores the transformative impact of AI-driven solutions in addressing pressing challenges in agriculture. By harnessing the power of deep learning and transfer learning, we can revolutionize traditional farming practices, ushering in a new era of precision agriculture that is both sustainable and resilient in the face of evolving agricultural threats.

IX. FUTURE WORK

Future work in the realm of paddy disease classification could focus on several avenues to further enhance the model's performance and applicability. Firstly, expanding the dataset to include a wider variety of paddy leaf diseases and incorporating more diverse environmental conditions would improve the model's robustness and generalization capabilities. This could involve collecting data from different geographical regions, varying weather conditions, and multiple growth stages of paddy plants. Additionally, incorporating data augmentation techniques to increase the diversity of the dataset, such as rotation, flipping, and scaling of images, could help the model better learn and adapt to different scenarios. In summary, future research in paddy disease classification should focus on expanding the dataset, exploring advanced deep learning architectures, and integrating real-time monitoring systems to improve the accuracy, efficiency, and sustainability of disease detection in paddy crops

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