AN EFFICIENT TRANSFER LEARNING APPROACH FOR RICE VARIETY IDENTIFICATION USING DENSE-INCEP NETWORK

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ABSTRACT

Rice is one of the most widely consumed staple foods across the globe, especially in Asian countries. Accurate identification of rice varieties is essential for improving quality control, seed selection, supply chain management, and ensuring food authenticity. Traditional methods of rice classification, often relying on manual observation, are time-consuming, error-prone, and inefficient for large-scale applications. To address these challenges, this project titled "Rice Varieties Identification using Deep Learning" proposes an automated, highly accurate classification system utilizing state-of-the-art deep learning techniques. The system is developed using Python for backend logic, with a user-friendly web interface built using HTML, CSS, and JavaScript, and deployed using the Flask web framework. Two powerful convolutional neural network models, DenseNet-121 and MobileNet, are implemented and evaluated. The DenseNet-121 model achieved a training accuracy of 99.0% and a test accuracy of 99.3%, while the lightweight MobileNet model outperformed with a training accuracy of 99.4% and a test accuracy of 99.5%, making it an ideal candidate for real-time, resource-efficient applications.The dataset used consists of 60,000 rice grain images, equally distributed across five classes: Arborio, Basmati, Ipsala, Jasmine, and Karacadag, with 12,000 images per class for training. The data preparation phase involved systematic steps including defining data directories, setting uniform image dimensions, image rescaling, structured loading, and preprocessing, ensuring high model generalization and accuracy.The results demonstrate that the proposed deep learning-based system can reliably distinguish between closely related rice varieties with high precision. The project not only contributes to agricultural digitalization but also paves the way for scalable deployment in food quality assurance, automated grain sorting, and supply chain monitoring applications.

INTRODUCTION

Rice (Oryza sativa) is one of the most important staple foods worldwide, serving as a primary source of nutrition for more than half of the global population. It plays a vital role in the agricultural economy and daily dietary needs, particularly in Asia, where countries like India, China, Indonesia, and others rely heavily on rice cultivation and consumption. Beyond its economic significance, rice is also culturally and nutritionally important, forming the foundation of meals in various traditional cuisines.

Rice is not a uniform crop; it is cultivated in hundreds of varieties, each with unique characteristics in terms of grain shape, size, texture, aroma, color, and cooking properties. These varieties are broadly categorized into two main subspecies—Indica and Japonica. Indica rice, typically long and slender, is commonly grown in tropical regions, while Japonica rice is short, round, and stickier when cooked, often cultivated in temperate climates.

Some widely recognized rice varieties include:

- **Basmati** – A long-grain, aromatic rice variety known for its fragrance and elongation after cooking.
- **Jasmine** – Another fragrant long-grain rice with a soft texture, commonly grown in Thailand.
- **Arborio** – A short-grain variety known for its creamy consistency, often used in Italian dishes like risotto.
- **Ipsala** and **Karacadag** – Regional rice types with distinct physical and cooking properties, often studied for classification research.

Identifying rice varieties accurately is essential for several reasons, including maintaining quality standards, ensuring proper seed selection, supporting export regulation compliance, and preventing adulteration. However, due to their subtle morphological differences, manual identification methods are often insufficient and prone to error. Therefore, automated systems based on deep learning and image processing have become vital in modern agricultural practices to ensure accurate and efficient classification of rice varieties

LITERATURE SURVEY

1) Rice-SeedNet: Rice seed variety identification using deep neural network

AUTHORS: R. Rajalakshmi, S. Faizal, S. Sivasankaran, and R. Geetha

Rice is one of the most important food crops in the South India. Many varieties of rice are cultivated in different regions of the India to meet the dietary needs of the ever-growing population. In spite of huge investment in terms of land, labour, raw materials and machinery, the farmers continuously face irrecoverable loss due to various reasons like climatic changes, drought situation and seed quality. In the current practice, the quality of the seeds is certified by the Seed Testing Laboratories (STL) and purity analysis is done manually by trained technicians. However, seed classification is not uniform across different labs, due to several factors like fatigue, eye-strain and personal circumstances of the technicians. Hence, automated rice seed variety identification becomes a crucial task for ensuring the quality and germination potential of rice crops. This research is focused on the application of Deep Neural Network (RiceSeedNet) combined with traditional image processing techniques to classify local rice seed varieties of southern Tamilnadu, India. The RiceSeed Image corpus is created for this purpose considering 13 local varieties. The captured RGB images of rice seed data consists of 13,000 images of local rice seed varieties, having 1000 images for each variety. To automate the rice seed varietal identification, vision transformer-based architecture RiceSeedNet is developed. The proposed RiceSeedNet is 97% accurate in classifying the 13 local varieties of rice seeds. The RiceSeedNet was also evaluated on a publicly available rice grain data set to study the performance of the proposed model across the different rice grain varieties. On this cross-data validation, RiceSeedNet is able to achieve 99% accuracy in classifying 8 varieties of rice grains on the public dataset.

2) Rice varieties classification using neural network and transfer learning with MobileNetV2

AUTHORS: V. Vania, A. Setyadi, I. M. D. Widyatama, and F. I. Kurniadi

Rice plays a vital role in global food security, feeding over 8 billion people worldwide. The classification of rice varieties based on visual characteristics, such as color, shape, and texture, is crucial for quality inspection and efficient farming practices. However, existing classification methods heavily rely on subjective and time-consuming human visual inspection, leading to errors and inefficiencies. This research paper explores the potential of deep learning approaches, specifically neural network and transfer learning with MobileNetV2, for accurate and efficient rice variety classification. The paper builds upon previous studies that have demonstrated the superiority of deep learning over traditional machine learning methods. Experimental results using a publicly available dataset of 75,000 rice grain images, labeled with five rice varieties, show that both the neural network and MobileNetV2 models achieve high accuracy rates. The neural network model is trained using stochastic gradient descent with 250 epochs, while the MobileNetV2 model leverages pretraining on the ImageNet dataset and is trained with the Adam optimizer for 10 epochs. The comparative analysis reveals that the MobileNetV2 model performs slightly better, benefiting from its ability to extract features from images learned from the large-scale ImageNet dataset. The findings highlight the potential of deep learning methods for rice variety classification, offering improved accuracy and efficiency in rice quality inspection. The choice between the neural network and MobileNetV2 models depends on the specific requirements and priorities of the application, with the neural network offering flexibility and transparency, and MobileNetV2 providing high accuracy through pre-trained feature extraction.

3) Transfer learning using mobilenet for rice seed image classification

AUTHORS: W. Agustiono, F. A. Safitri, W. Setiawan, and C. Chan

Rice is the world's primary source of carbohydrates, especially in Asia. Quality rice requires good seed breeding. In this research, we classified rice seeds. The experiment using public data consists of five classes. Each class contains 2,000 images. The total amount of image data is 10,000. Classification uses mobileNet, which consists of 13 depthwise separable convolutions consisting of depthwise (DW) and pointwise (PW) convolutional layers. Each DW and PW is followed by batch normalization and Rectified Linear Unit activation. At the end, there is Global Average pooling and two dense layers. The trial uses transfer learning with initial weights from imageNet. The first to twelfth convolutional layers freeze. That is, they do not train the weights in them. On the 13th or last convolutional layer, fine-tuning is carried out. Experimental data is divided into training, validation, and testing. The testing results show that accuracy is 99.55%, precision 99.55%, recall 99.08%, and f1-score 99.31%.

4) Deep learning based models for paddy disease identification and classification: A systematic survey

AUTHORS: M. Tasfe, A. Nivrito, F. Al Machot, M. Ullah, and H. Ullah

Automated early detection and classification of paddy diseases help in applying treatment efficiently according to the detected diseases. Early detection also minimises the usage of chemical substances and pesticides and hinders the spread of the disease to healthy crops. On a broader scale, it aids in halting the global spread of diseases. Thus, it ultimately promotes healthier rice crops and increased yield. In this survey paper, we present a thorough exploration of deep learning (DL) models for the classification of paddy diseases. Our paper delves into the motivation behind this research study, reveals different paddy diseases and their associated symptoms, and unravels various deep-learning models employed for disease detection. We have also discussed strategies used by researchers for improving the performance of DL models, along with adaptations tailored for application-specific contexts. Additionally, we illustrate relevant research findings, explore datasets utilised in this domain, and analyse approaches for data augmentation. Through an exhaustive investigation, we emphasise existing research gaps, challenges, and open issues, concluding in a discussion on avenues for future exploration.

5) Computer vision and machine learning analysis of commercial Rice grains: A potential digital approach for consumer perception studies

AUTHORS: A. Aznan, C. Gonzalez Viejo, A. Pang, and S. Fuentes

Rice quality assessment is essential for meeting high-quality standards and consumer demands. However, challenges remain in developing cost-effective and rapid techniques to assess commercial rice grain quality traits. This paper presents the application of computer vision (CV) and machine learning (ML) to classify commercial rice samples based on dimensionless morphometric parameters and color parameters extracted using CV algorithms from digital images obtained from a smartphone camera. The artificial neural network (ANN) model was developed using nine morpho-colorimetric parameters to classify rice samples into 15 commercial rice types. Furthermore, the ANN models were deployed and evaluated on a different imaging system to simulate their practical applications under different conditions. Results showed that the best classification accuracy was obtained using the Bayesian Regularization (BR) algorithm of the ANN with ten hidden neurons at 91.6% (MSE = <0.01) and 88.5% (MSE = 0.01) for the training and testing stages, respectively, with an overall accuracy of 90.7% (Model 2). Deployment also showed high accuracy (93.9%) in the classification of the rice samples. The adoption by the industry of rapid, reliable, and accurate methods, such as those presented here, may allow the incorporation of different morpho-colorimetric traits in rice with consumer perception studies.

SYSTEM ANALYSIS

EXISTING SYSTEM:

- The existing system of Rice Variety Identification focuses on accurately classifying rice grain varieties using an advanced deep learning architecture. In this system, the authors introduce a hybrid model called DENS-INCEP, which effectively combines DenseNet-201 as the primary feature extractor with the Inception module for capturing multi-scale shape-related features of rice grains.
- The workflow of the existing system begins with the acquisition of rice grain images, followed by preprocessing steps such as grayscale conversion, binary thresholding, image correction, and edge detection. The dataset used in the base paper includes images of five rice varieties: Arborio, Basmati, Ipsala, Jasmine, and Karacadag.. The data is processed and fed into the DENS-INCEP architecture for training and classification.
- DenseNet-201, known for its dense connectivity and efficient feature reuse, serves as a robust backbone in the model, while the Inception module enhances feature extraction by analyzing spatial features at multiple scales. The architecture is trained and validated using the TensorFlow and Keras frameworks, achieving a high overall classification accuracy of 99.94%. Performance is further validated using standard metrics such as accuracy, sensitivity, specificity, confusion matrix, and ROC curves.
- The system is designed to contribute to real-world applications in rice grain quality inspection and classification, supporting sustainable agriculture and food traceability. Its architecture is optimized for high accuracy and efficient training, showcasing the potential of transfer learning in agricultural image classification tasks.

DISADVANTAGES OF EXISTING SYSTEM:

- High Computational Complexity: The combination of DenseNet-201 and the Inception module results in a deep and complex model architecture. This demands significant computational resources, both in terms of memory and processing power, making it less suitable for deployment on low-end or edge devices such as mobile phones or embedded systems.
- Large Model Size: Due to the extensive number of layers and parameters in DenseNet-201, the resulting DENS-INCEP model has a relatively large size (~89.5 MB). This increases loading times, requires more storage, and limits its portability, especially in bandwidth-constrained or storage-sensitive environments.
- Longer Training and Inference Time: The depth and complexity of the model contribute to longer training durations and slower inference speeds. This can be a drawback in scenarios that demand real-time predictions or frequent model updates.
- Limited Focus on Lightweight Deployment: The system is primarily designed for high-performance GPU environments. It lacks optimization for deployment in real-world agricultural fields where compact, efficient, and energy-conserving solutions are often required.
- Absence of Real-Time Application Demonstration: The base paper emphasizes model architecture and performance metrics but does not include an interactive or deployable application (e.g., web or mobile-based classifier) for end-user use. This limits its immediate practical applicability in real-world scenarios.

- No Visual Interpretability Features: Although the model performs well in classification tasks, it does not integrate any explainability methods such as Grad-CAM, which could help in understanding the model's focus areas and build user trust in critical use cases.

By addressing these limitations, a more efficient, lightweight, and practical solution can be developed for real-time rice variety classification and deployment in diverse environments.

PROPOSED SYSTEM:

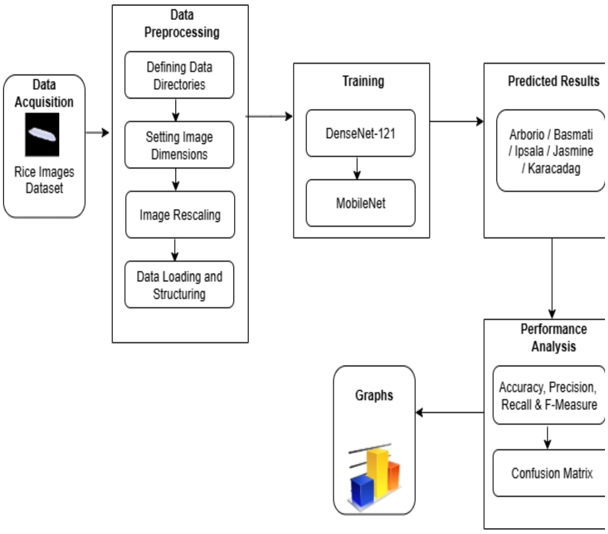
- The proposed system aims to build an efficient and accurate rice variety classification model by leveraging deep learning techniques using DenseNet-121 and MobileNet architectures. This system is designed to classify five types of rice grains—Arborio, Basmati, Ipsala, Jasmine, and Karacadag—based on their visual characteristics using high-resolution image data.
- The backend of the system is developed using Python, with the frontend built using HTML, CSS, and JavaScript, and the entire application is deployed using the Flask web framework. The rice grain images are preprocessed through a series of data preparation steps, which include defining data directories, setting image dimensions, rescaling pixel values, and loading structured datasets. These steps ensure consistent input data for training the models.
- The dataset used contains a total of 60,000 images, with each rice variety having 12,000 training images. The images are uniformly resized and normalized before being fed into the deep learning models. Two different CNN-based models are implemented:
  - DenseNet-121: A moderately deep neural network known for its dense connectivity, used as a feature extractor and classifier.
  - MobileNet: A lightweight architecture designed for mobile and edge-device applications, optimized for efficiency and speed.
- Both models are trained separately, and their performances are evaluated using training and testing datasets. Standard classification metrics such as accuracy, confusion matrix are used for assessing the system's effectiveness. The entire system is integrated into a web-based interface, allowing users to upload rice grain images and receive immediate classification results.
- The architecture of the proposed system is modular, consisting of components for data preprocessing, model training, performance evaluation, and real-time prediction. This modular design supports ease of experimentation, scalability, and future integration of additional functionalities.

ADVANTAGES OF PROPOSED SYSTEM:

- Lightweight and Efficient Models: By utilizing DenseNet-121 and MobileNet, the system maintains high classification accuracy while significantly reducing model size and computational complexity compared to deeper architectures like DenseNet-201. This makes it highly suitable for environments with limited processing power.
- High Accuracy with Reduced Complexity: Despite using more compact models, the system achieves excellent performance—DenseNet-121 records a test accuracy of 99.3%, and MobileNet achieves 99.5%. This demonstrates that complex architectures are not always necessary to achieve top-tier results.
- Faster Training and Inference Times: The shallower depth and optimized design of the selected models allow for quicker training cycles and faster prediction times, making the system more practical for real-time applications and frequent updates.
- Deployment-Ready for Web and Mobile Platforms: The system is developed using Flask and integrates a user-friendly web interface with HTML, CSS, and JavaScript, enabling smooth deployment on various platforms. The use of MobileNet further supports deployment on mobile and edge devices.
- Reduced Resource Requirements: Compared to the base model, the proposed system requires less memory and processing power, making it ideal for use in resource-constrained environments such as agricultural fields, local processing centers, or handheld devices.
- Scalability and Flexibility: The modular design of the system allows easy updates, such as adding new rice varieties or retraining with additional datasets. This ensures long-term scalability and adaptability to changing agricultural needs.
- Improved Real-World Applicability: With a simple and interactive web-based application, the system becomes more accessible to end-users like farmers, quality inspectors, or distributors who can benefit from fast and accurate rice variety classification.
- Supports Real-Time Prediction: The low-latency inference capability of the models makes the system suitable for real-time prediction scenarios, where instant feedback is essential for sorting, packaging, or export quality verification processes.

By incorporating accuracy, efficiency, and deployability, the proposed system provides a robust and practical solution for modern agricultural challenges in rice variety identification.

IMPLEMENTATION



MODULES:

Data Collection:

- ❖ In the first module of the Rice Varieties Identification using Deep Learning, we make the data collection process. This is the first real step towards the real development of a deep learning model, collecting data. This is a critical step that will cascade in how good the model will be, the more and better data that we get; the better our model will perform
- ❖ There are several techniques to collect the data, like web scraping, manual interventions. The dataset is located in the model folder. The dataset is referred from the popular dataset repository called kaggle. The following is the link of the dataset:
- ❖ Kaggle Dataset Link:

https://www.kaggle.com/datasets/jayaprakashpondy/rice-image

Dataset:

- ❖ In this module, Set up two main directories: training, and testing. Training, and testing directories, create subdirectories is 5 class label.
- ❖ Place the images into their respective class directories based on their labels. Each image should be placed in the directory corresponding to its class label and By organizing the dataset in this structure, it becomes straightforward to load the data into your deep learning framework for training and testing purposes and Total dataset size is 75,000.

Data Preparation:

- ❖ During the data preparation stage, it is crucial to preprocess the data to ensure it is suitable for training. This involves tasks such as resizing images to a standard size, normalizing pixel values, and encoding labels if necessary. To achieve this, the ImageDataGenerator from Keras can be utilized. For instance, to resize images to a standard size of 224x224 pixels, the Target_size parameter can be set to (img_height, img_width) = (224, 224).
- ❖ Additionally, pixel values can be normalized by setting the rescale parameter to 1./255, which scales the pixel values to be between 0 and 1. Furthermore, data augmentation techniques such as random shear and zoom can be applied to enhance the training data. By leveraging these techniques, the data can be effectively preprocessed to improve the performance of the deep learning model.

Feature Extraction:

- ❖ For models like MobileNet and DenseNet121, which come pre-trained with feature extraction layers, explicit feature extraction may not always be necessary. By setting trainable = False, we freeze these pre-trained layers, allowing them to retain their learned representations while preventing further updates during training.
- ❖ In the context of MobileNet and DenseNet121, setting trainable = False ensures that the weights of the feature extraction layers remain fixed during training. This approach is commonly used in transfer learning scenarios, where the pre-trained model is fine-tuned on a new dataset for a specific task, such as image classification or object detection.
- ❖ By adopting this strategy, we strike a balance between leveraging powerful pre-trained representations and adapting the model to our specific dataset, ultimately improving both training efficiency and model performance.

Splitting the dataset:

- ❖ Divide your dataset into training and validation to evaluate your model's performance. Typically, you might use an 80-20 split, but this can vary based on your dataset size and specific requirements.

Model Selection:

- ❖ The training module is responsible for training the deep learning models using the preprocessed data. It implements two popular architectures: MobileNet and DenseNet121.

MobileNet:

- MobileNet is a lightweight and efficient convolutional neural network architecture designed for mobile and embedded devices. It uses depth-wise separable convolutions to build deep neural networks while maintaining a small model size and low computational complexity. MobileNet consists of an initial fully convolutional layer, followed by a series of inverted residual blocks with linear bottlenecks. These blocks use depth-wise convolutions to filter features and 1x1 convolutions to combine features. The network ends with a final convolution layer and global average pooling.

DenseNet121

- **DenseNet121** is a deep convolutional neural network that introduces dense connections between layers to improve information flow and learning efficiency. Unlike traditional architectures where each layer connects only to the next, DenseNet connects each layer to every other layer in a feed-forward fashion. This design allows the network to reuse features, leading to improved accuracy and reduced redundancy. DenseNet121 is composed of four dense blocks, separated by transition layers that perform downsampling using 1x1 convolutions and average pooling. Each layer in a dense block receives feature maps from all preceding layers, enhancing gradient flow during training. The model uses batch normalization and ReLU activation after each convolution. It has a total of 121 layers, including convolutional, pooling, and fully connected layers. DenseNet121 is known for its parameter efficiency, making it faster to train than deeper networks with similar performance. It also helps mitigate the vanishing gradient problem seen in very deep networks.

Training the Model:

- To train the models, the training module first loads the pre-trained weights for MobileNet and DenseNet121 from the dataset. It then adds a global average pooling layer and a fully connected layer with the appropriate number of classes for the specific task. The base layers of the pre-trained models are frozen by setting their trainable flag to False, allowing only the added layers to be trained.

- The training process involves optimizing the model parameters using a suitable optimization algorithm, such as Adam or SGD, and a loss function appropriate for the task (e.g., categorical cross-entropy for classification). The training data is fed to the model in batches, and the gradients are computed and used to update the model weights. The training process continues for a specified number of epochs or until a certain performance metric is achieved on a validation set.

- After training, the module saves the trained models for future use in the prediction and evaluation modules. The saved models can be loaded and used for inference on new data or fine-tuned on additional datasets if needed.

Analyze and Prediction:

- Once training is complete, analyze the training process (e.g., loss curves) and make predictions on your validation set to assess the model's performance.

Accuracy on test set:

- Once the model is trained, it needs to be evaluated for its performance. This module involves splitting the dataset into training and testing subsets and assessing the model's accuracy, precision, recall, and F1-score.
- The MobileNet architecture achieves a Training accuracy of 99.4 % and validation accuracy of 99.5%. The DenseNet121 architecture attains a Training accuracy of 99.0% and validation accuracy of 99.3%

Saving the Trained Model:

- Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into an .h5 or .pkl file using a library like pickle.
- Make sure you have pickle installed in your environment.
- Next, let's import the module and dump the model into .pkl file.

Prediction Module:

- Develop a prediction module to make predictions using the trained MobileNet and DenseNet121 model. This module should take input images, preprocess them as necessary, and output predictions.

Model Evaluation Module

- This module evaluates the performance of the trained models using the testing dataset. It calculates accuracy metrics and other performance indicators to assess model effectiveness.

- Evaluate model accuracy, precision, recall, and F1-score.
- Generate confusion matrices for both models.
- Compare the performance of the MobileNet and DenseNet121.
- Accuracy, precision, recall, and F1-score are used to evaluate model performance.

CONCLUSION

The project titled "Rice Varieties Identification using Deep Learning" successfully demonstrates an effective and efficient approach to classifying rice grains using modern deep learning techniques. By implementing and evaluating two advanced convolutional neural network models—DenseNet-121 and MobileNet—the system achieves high classification accuracy while maintaining lightweight architecture and fast processing speeds. Comprehensive preprocessing steps, including image rescaling and structured data loading, ensured data consistency and enhanced model performance. The DenseNet-121 model achieved a training accuracy of 99.0% and a testing accuracy of 99.3%, while the MobileNet model surpassed this with a training accuracy of 99.4% and testing accuracy of 99.5%. These results highlight the capability of deep learning models to effectively capture and distinguish subtle morphological features among closely related rice varieties such as Arborio, Basmati, Ipsala, Jasmine, and Karacadag. The system was developed using Python for backend logic and Flask as the web framework, along with an interactive frontend built using HTML, CSS, and JavaScript. This integration allows users to upload rice grain images and receive instant classification results through a web-based interface, offering practical usability and accessibility. Overall, the project provides a scalable, accurate, and resource-efficient solution for rice variety classification, with strong potential for application in agricultural quality control, automated sorting, and supply chain optimization.

FUTURE WORK:

While the proposed system demonstrates high accuracy and efficiency in rice variety identification, several opportunities exist to further enhance its functionality, scalability, and real-world applicability:

- Expansion to More Rice Varieties: The current system is limited to five rice classes. Future enhancements could include expanding the dataset to cover a broader range of rice varieties commonly found in different regions, thereby increasing the model's generalization and global relevance.
- Integration of Explainable AI Techniques: Incorporating visualization tools like Grad-CAM or Layer-wise Relevance Propagation (LRP) can help interpret model decisions. This would improve transparency and user trust by showing which grain features influenced the prediction.
- Deployment on Mobile and Edge Devices: Further optimization of the MobileNet model for deployment on Android smartphones, Raspberry Pi, or NVIDIA Jetson devices can facilitate real-time classification in the field, benefiting farmers and supply chain handlers.
- Support for Multi-Language Interfaces: Enhancing the web application with support for regional languages can improve accessibility and usability for local users, especially in agricultural communities.
- Incorporation of Real-World Image Variability: Future versions of the model can be trained on images captured in diverse lighting, backgrounds, and angles to better handle real-world variations and environmental noise.
- Automated Quality Grading: In addition to identifying the rice variety, future work can include developing a grading system to assess rice grain quality based on size, color uniformity, and damage detection.
- Hybrid Ensemble Models: Exploring ensemble techniques by combining predictions from DenseNet121, MobileNet, and possibly other lightweight models may lead to even more robust performance under challenging conditions.
- Cloud-Based API Service: Developing a cloud-based API that integrates the classification logic can enable third-party platforms, mobile apps, and industrial systems to access the rice identification service remotely and on-demand.

By implementing these future enhancements, the system can evolve into a more powerful, intelligent, and accessible solution for modern agricultural automation and food quality assurance.

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