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Implementation of Convolutional Neural Network for Rice Leaf Disease Classification to Optimize Farmers' Decision-Making

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Abstract

This study aims to develop a rice leaf disease classification model using a Convolutional Neural Network (CNN) with the MobileNetV2 architecture to assist farmers in making accurate decisions. A quantitative approach was employed through experimental methods involving the processing of 3,829 digital images from a publicly available dataset. The results indicate that the developed CNN model effectively classifies six categories of rice leaf conditions with 91% accuracy and was successfully integrated into a web-based application. This research concludes that the implementation of the MobileNetV2 architecture provides a rapid and efficient approach to plant disease diagnosis compared to traditional manual methods.

Keywords: *Convolutional Neural Network; Deep Learning; Image Classification; MobileNetV2; Rice Leaf Disease*

1. Introduction

The rice agriculture sector plays a crucial role as a primary food source; however, its productivity is frequently hindered by significant plant disease outbreaks [1][2][3]. Traditional rice leaf disease identification, which relies on manual visual observation by farmers, possesses inherent limitations such as high subjectivity and the risk of misdiagnosis, potentially leading to inappropriate treatments [4]. Consequently, there is an urgent need for technology capable of providing objective and accurate early detection to minimize crop failure.

Advances in artificial intelligence, particularly Computer Vision, have contributed significantly to the digital transformation of agriculture [5]. Convolutional Neural Networks (CNNs) represent one of the most effective methods for image classification, as they facilitate automated feature extraction from visual plant data [6][7]. Despite their high performance, CNNs present challenges regarding substantial computational requirements when deployed on resource-constrained devices [8].

To address these limitations, the MobileNetV2 architecture provides an efficient solution through depthwise separable convolutions, which reduce computational load without drastically compromising accuracy [9]. While previous studies have applied CNNs for disease classification, gaps remain concerning accessibility for end-users specifically farmers in the field [1][10][11]. Integrating models into web-based applications serves as a crucial bridge, enabling Deep Learning technology to be accessed in real-time via standard web browsers.

Based on this background, this study aims to implement a CNN using the MobileNetV2 architecture for classifying six rice leaf condition categories, integrated into a web-based application. This research is expected to provide a practical solution for farmers in making accurate and efficient disease management decisions, while serving as a reference for future development of digital crop monitoring systems.

2. Literature Review

2.1. Fundamental Concepts of Image Processing and Deep Learning

Digital image processing is the manipulation of visual data to extract essential information, which in this study is employed to identify disease symptoms in plants [12]. Technological transformation in agriculture currently relies heavily on the ability of machines to learn patterns autonomously. Deep Learning, as a subfield of artificial intelligence, enables the development of models capable of recognizing data representations hierarchically through complex layers of artificial neural networks [4][13].

2.2. Convolutional Neural Network (CNN)

The primary method employed for image classification in this study is the Convolutional Neural Network (CNN). The architecture of CNNs is characterized by a hierarchical structure comprising convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for final classification [14]. A fundamental advantage of CNNs over conventional machine learning approaches lies in their inherent capacity for automated spatial feature learning; this mechanism effectively eliminates the necessity for complex and labor-intensive manual feature engineering. Such capability is pivotal in identifying the intricate textures and subtle color patterns manifested in infected rice leaf lesions.

2.3. MobileNetV2 Architecture

To address the requirement for a lightweight and efficient application, this study employs the MobileNetV2 architecture. This architecture leverages depthwise separable convolutions, which significantly reduce the number of computational parameters without drastically compromising accuracy [9]. Furthermore, the utilization of inverted residual blocks and linear bottlenecks facilitates optimal model performance on resource-constrained devices, particularly in the context of web-based system implementation.

2.4. User Interface and Application Programming Interface (API) Implementation

The practical implementation of the model necessitates a robust integration between frontend and backend architectures. The React.js framework was selected to construct a responsive and interactive user interface (UI) [15][16]; concurrently, Flask was utilized to develop RESTful API services that facilitate seamless data communication between the frontend and the Python-based classification model [17]. Furthermore, the aesthetic integrity and navigational efficiency of the application are supported by Tailwind CSS, which enables the rapid development of a consistent and scalable design system [18].

2.5. Model Evaluation and Confusion Matrix Analysis

The performance of the developed model is evaluated using standard metrics derived from a confusion matrix. This evaluation encompasses the measurement of accuracy, precision, and recall to ensure that the model demonstrates not only high overall accuracy but also balanced recognition capability across all disease categories [9][19].

3. Research Methods

3.1. Research Design and Dataset Acquisition

This research constitutes an experimental study employing Deep Learning, with a specific focus on developing a digital image classification system. The primary data source consists of secondary data obtained from the Kaggle platform, specifically the Rice Disease Dataset, comprising 3,829 digital images of rice leaves. The scope of this study is delimited to six distinct plant health categories, namely Bacterial Leaf Blight, Brown Spot, Healthy Rice Leaf, Leaf Blast, Leaf Scald, and Sheath Blight.

3.2. Model Development Workflow

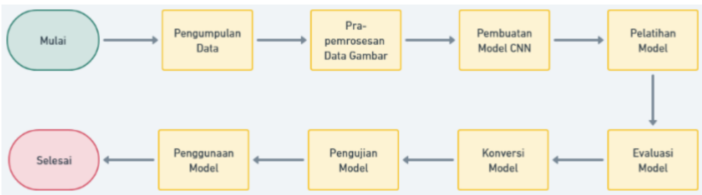

Fig. 1: Research Workflow

The research procedure is executed through a series of systematic phases, ranging from data preparation to system implementation. These phases are structured as follows:

1. Data Preprocessing. All images are resized to 224 x 224 pixels to conform to the standard input specifications of the MobileNetV2 architecture.
2. Model Training. The training process is conducted using the Adam optimizer, with a learning rate initialized at 0.001 to ensure the stability of weight updates. The training is executed over 45 epochs with a batch size of 64 samples per iteration to achieve an optimal balance between memory efficiency and gradient stability. To mitigate the risk of overfitting, early stopping and learning rate reduction mechanisms are implemented; these functions adaptively decrease the learning rate when validation performance demonstrates stagnation.
3. System Implementation. The trained model is integrated into a web-based application architecture, utilizing Flask as the backend framework and React.js for the frontend interface development.

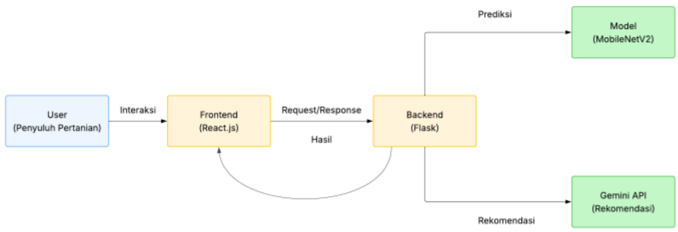

Fig. 2: System Architecture

3.3. Performance Evaluation Metrics

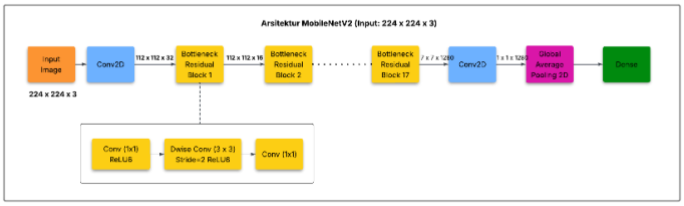

Fig. 3: MobileNetV2 Architecture

The primary research instrument utilized in this study is a modified MobileNetV2 architecture, specifically tailored for the classification of six categories of rice leaf diseases. The comprehensive structural details of the architecture, spanning from the input to the output layers employed in this experiment, are visually illustrated in Figure 3.

To ensure research reliability and replicability, the technical hyperparameter configurations are summarized in Table 1. The selection of these parameters is predicated on the necessity to strike an optimal balance between processing latency and classification accuracy for deployment on web-based devices.

Tabel 1: Experimental Configuration Parameters

Parameter	Value
Backbone Architecture	MobileNetV2
Image Input Size	224 x 224 pixels
Learning Rate	0.001
Batch Size	64
Optimizer	Adam
Dropout Rate	0.5
Epochs	45

3.4. Data Analysis Techniques

Data analysis is conducted quantitatively by monitoring the progression of loss and accuracy values throughout the 45 training epochs. Subsequently, the training and validation metrics are visualized to assess the stability of the model's learning process and to detect any indications of overfitting or underfitting.

4. Results and Discussion

4.1. Experimental Results

Model performance evaluation was conducted by assessing classification accuracy on a previously unseen test dataset. The results derived from the 45 training epochs demonstrate that the MobileNetV2-based Convolutional Neural Network (CNN) achieved an overall accuracy of 91%. A comprehensive summary of the model's performance across all rice leaf disease categories is presented in Table 2.

Tabel 2: Model Performance Results per Category

Class	Precision	Recall	F1 Score	Support
Bacterial Leaf Blight	0.83	0.94	0.88	64
Brown Spot	0.96	0.86	0.91	64
Healthy Rice Leaf	0.98	0.98	0.98	65
Leaf Blast	0.87	0.86	0.87	64

Leaf Scald	0.90	0.87	0.89	63
Sheath Blight	0.94	0.97	0.95	63
Accuracy			0.91	383
Macro Avg	0.92	0.91	0.91	383
Weighted Avg	0.92	0.91	0.91	383

Beyond quantitative metrics, the distribution of true and false predictions is visualized through the Confusion Matrix depicted in Figure 4. This visualization facilitates a meticulous analysis of the model's ability to discern distinct visual characteristics across different disease categories.

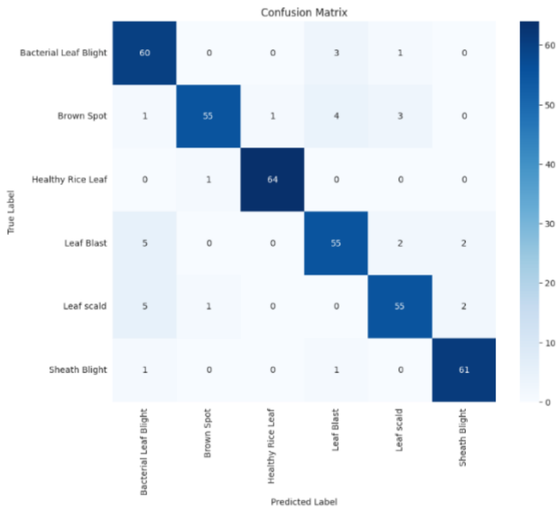

Fig. 4: Confusion Matrix for Performance Evaluation

4.2. Comparative Analysis with Previous Studies

The findings of this study demonstrate that the utilization of MobileNetV2 provides an optimal balance between classification accuracy and processing efficiency. The achieved accuracy of 91% is consistent with previous research reporting high performance levels in comparable architectures, such as Inception V3 (93.75%) and MobileNetV1 (92.2%). A significant advantage of this system lies in its integration with a web-based platform to enhance accessibility for farmers, a dimension that has remained relatively under-explored in prior literature.

4.3. Discussion and Future Directions

The efficacy of the model in classifying rice leaf diseases yields significant practical implications for the agricultural sector. By providing rapid and precise diagnostics, this system facilitates a paradigm shift for farmers, transitioning from subjective manual assessments toward AI-driven, data-centric methodologies. Building upon these findings, future directions will involve the development of targeted treatment recommendation features based on model predictions to more effectively mitigate the risk of crop failure.

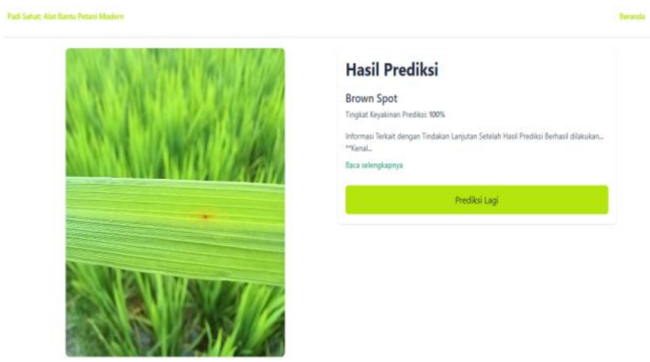

Fig. 5: System Interface and Decision Support

4.4. Research Limitations

While the results obtained are highly promising, this study is subject to several limitations. The dataset employed is restricted to images characterized by relatively uniform backgrounds and lighting conditions. Consequently, the model's generalization capabilities under more dynamic field conditions such as extreme illumination or complex backgrounds warrant further enhancement in future studies through the inclusion of more heterogeneous datasets.

5. Conclusion

This research demonstrates the high efficacy of a modified MobileNetV2 architecture, achieving an exceptional 91% accuracy in classifying six rice leaf diseases. The results confirm that the model successfully balances computational efficiency with diagnostic precision, making it highly viable for real-world deployment. The primary novelty of this study lies in the successful transition of deep learning theory into a functional web-based ecosystem (Flask and React.js), bridging the gap between laboratory experimentation and accessible decision-support tools for farmers.

To advance the sustainability of this system, future directions will focus on enhancing the model's generalization robustness by incorporating more heterogeneous datasets from diverse environmental conditions. Additionally, integrating this framework with IoT sensors and mobile edge devices is essential to establish a more proactive and practical precision farming paradigm.

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