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Complex-Valued Neural Network And Fuzzy Inference System For Image Diagnosis Of Rice Leaf Diseases

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Abstract

Rice serves as a crucial food crop and holds significant importance in Indonesia's agricultural sector. so the health of rice leaves determines the productivity of the crop. Serious problems such as crop failure often occur due to leaf disease attacks caused by pests or unfavorable climatic factors. Controlling these diseases requires proper knowledge so as not to cause negative impacts on the ecosystem due to misdiagnosis. This research develops a Complex-Valued Neural Network (CVNN) and Fuzzy Inference System (FIS) based method to identify the type of disease and determine its severity. CVNN was used to classify leaf images based on detected visual traits, while FIS analyzed the relationship between these traits and disease severity using fuzzy rules constructed from expert data or input. The results show that CVNN provides superior performance compared to CNN, CVNN model with an accuracy of 92%, where all classes produce high and balanced. While the CNN model also provides satisfactory results with an accuracy of 89%, although there is still an imbalance in some classes. The results of the FIS model on the image The severity of the image of rice leaf disease is the most high category in the leaf blast class is the highest of all classes. The combination of CVNN and FIS model proves that this hybrid approach is effective to support diagnosis, so it can help farmers in making early and precise decisions.

Keywords: Leaf Disease Rice; Classification; Detection; CVNN; Fuzzy Inference System

Abstrak

Padi merupakan tanaman pangan yang sangat penting dan memegang peranan penting dalam sektor pertanian di Indonesia, jadi kesehatan daun padi sangat menentukan produktivitas tanaman. Masalah serius seperti gagal panen sering terjadi akibat serangan penyakit daun yang disebabkan oleh hama atau faktor iklim yang tidak mendukung. Pengendalian penyakit ini membutuhkan pengetahuan yang tepat agar tidak menimbulkan dampak negatif terhadap ekosistem akibat kesalahan diagnosis. Penelitian ini mengembangkan metode berbasis Complex-Valued Neural Network (CVNN) dan Fuzzy Inference System (FIS) untuk mengidentifikasi jenis penyakit serta menentukan tingkat keparahannya. CVNN digunakan untuk mengklasifikasikan gambar daun berdasarkan ciri visual yang terdeteksi, sementara FIS menganalisis hubungan antara ciri-ciri tersebut dengan tingkat keparahan penyakit menggunakan aturan fuzzy yang disusun dari data atau masukan pakar. Hasil penelitian menunjukkan bahwa CVNN memberikan performa yang lebih unggul dibandingkan dengan CNN, Model CVNN dengan menghasilkan akurasi sebesar 92% , di mana semua kelas menghasilkan yang tinggi serta seimbang. Sedangkan model CNN juga memberikan hasil yang memuaskan dengan akurasi sebesar 89% , meskipun masih terdapat ketidakseimbangan pada beberapa kelas. Hasil dari model FIS pada citra Tingkat keparahan citra penyakit daun padi kategori paling banyak kategori tinggi pada kelas leaf blast adalah yang tertinggi dari semua kelas. Kombinasi dari model CVNN dan FIS membuktikan bahwa pendekatan hibrid ini efektif untuk mendukung diagnosa, sehingga dapat membantu petani dalam pengambilan keputusan lebih awal dan tepat.

Kata kunci: Penyakit Daun Padi; Klasifikasi; Deteksi; CVNN; Fuzzy Inference System

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INTRODUCTION

Rice (Oryza sativa) is one of the main food commodities that occupies the third position after corn and wheat among various types of grains (Zhou et al. 2019). The agricultural sector has an important role in a country's economy, especially in providing food needs for the community (Liang et al. 2019) . Rice serves as an important staple food in many countries. As the world's population increases, the consumption and demand for rice also increases (Dewi, Anjarwati, and Cholissodin 2017).

Currently, artificial intelligence technology has made significant contributions in various sectors to solve various problems, including in the agricultural sector. The most popular modern approaches include the application of machine learning and deep learning by utilizing various algorithms to improve the accuracy and ability to detect and diagnose plant diseases (Xu et al. 2022).

Leaf disease classification technology powered by artificial intelligence offers valuable support to farmers by speeding up the detection process of diseases affecting rice plant leaves. One effective approach involves utilizing the Complex-Valued Neural Network (CVNN) (Bukhari 2024). The advanta ge of CVNN lies in its ability to integrate and understand features efficiently, so as to identify small differences that often occur in rice leaf diseases. Experimental results show that CVNN can outperform the Convolutional Neural Network (CNN) model with significant value in terms of higher accuracy (Wardhana, Wang, and Sibuea 2023).

In the literature review, one of the studies relevant to this topic is Krisdianto's work proposing the utilization of image processing technology and artificial intelligence to assist farmers in automatically detecting diseases in rice plants. The method used is based on the YOLO algorithm, which is known to be effective in real-time object detection tasks. Based on tests conducted with a dataset of 661 images, the system achieved an average accuracy rate of 77% as measured using the confusion matrix. The data has been divided into training, validation, and test data. The results show that the YOLO algorithm is reliable enough to be used as a tool for early diagnosis of rice plant diseases, so that it can provide real benefits to farmers in an effort to increase yields and efficiency in the cultivation process (Krisdianto, Elta Sonalitha, and Yandhika Surya Akbar Gumilang 2024).

Based on the existing background and previous literature review, the author conducted research aimed at supporting the agricultural sector, especially for rice farmers. This research aims to apply Complex-Valued Neural Network (CVNN) in the classification of rice leaf diseases, combined with Fuzzy Inference System (FIS), so that it is expected to produce a system that is able to accurately recognize various types of diseases based on observed characteristics and identify clear relationships between these characteristics and disease severity. With early and accurate diagnosis, economic losses due to disease can be minimized. This helps in reducing the overuse of pesticides.

RESEARCH METHODS

This research uses a machine learning-based approach, the research methodology is carried out in stages. The sequence of research steps is explained through a research flow chart during the research process. The research methodology flowchart shown in Figure 1 illustrates the main stages which include data collection, building model architecture, model training, and evaluating model performance.

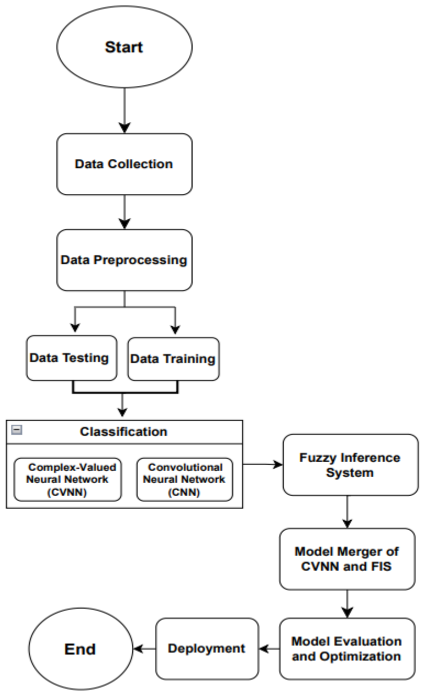

Figure 1. Research Stages

Types of research

This research uses a quantitative approach by applying the Complex-Valued Neural Network and Fuzzy Inference System algorithms to classify images and predict the severity of rice leaf disease

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images. This approach was chosen due to its ability to handle complex image data and provide high accuracy in classification and prediction.

Time and Place of Research

Data collection was conducted in October 2024 through rice production farms used in the form of dataset images obtained manually using a camera. The process of data analysis and model development was conducted in Surabaya, East Java during the period of October to November 2024.

Deep learning

Deep learning is a machine learning technique that involves many layers of artificial neural networks, which are used to process data incrementally. Deep learning is a subset of machine learning that uses neural networks to solve various complex problems. Deep learning is also part of machine learning but has its own network, called deep because the algorithm structure has hundreds of layers of neural networks. One of the advantages of deep learning is that it can help solve quite complex problems, such as the ability to recognize an image, recognize sounds, and even mimic the workings of the human brain through the artificial nerves in the algorithm (Nurdiawan 2018).

Complex-Valued Neural Network

The Complex-Valued Neural Network (CVNN) is designed to handle input data in complex number form by utilizing complex-valued weights, thresholds, and activation functions, resulting in complex-valued outputs (Rahmawati, Muhaimin, and Prasetya 2024). One of its key advantages lies in its enhanced capability to accurately process data that contains both real and imaginary components—something that standard neural networks often struggle with. By leveraging complex-valued elements throughout its architecture, CVNN significantly improves the network's capacity to analyze and interpret intricate data structure (Barrachina et al. 2023).

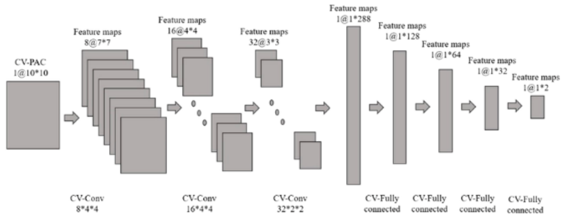

Figure 2. Summary of CVNN Model

A key feature of Complex-Valued Neural Networks (CVNNs) is their capability to effectively manage complex-valued data. Unlike traditional neural networks, CVNNs are better equipped to interpret and process information that includes both real and imaginary components. These networks are composed of interconnected perceptrons that operate with complex values. The training of CVNNs is conducted using a complex-valued backpropagation algorithm, where all elements—inputs, weights, biases, and outputs—are represented as complex numbers (Putri, Prasetya, and Fahrudin 2024). The input Un to the complex-valued neuron n is defined as follows:

$$Un = \sum_{m} WnmXm + Tn \quad (1)$$

Description:
Wnm = weight (complex value) connecting complex-valued neuron n with complex-valued neuron mm
Xmm = input (complex value) of complex-valued neuron mm
Tn = threshold (complex value) of neuron n

Convolutional Neural network

A Convolutional Neural Network (CNN) is a type of artificial neural network that uses convolution operations in its architecture. The convolution function in CNN is used to extract important features from the input data. The advantage of the CNN method is that it can automatically extract important features from each image without human assistance, besides that the CNN method is also more efficient than other neural network methods, especially for memory and complexity. Meanwhile, the disadvantages of the CNN method are that it requires a lot of training data, a time-consuming training process, and overfitting (Jinan, Hayadi, and Utama 2022). CNN combines artificial neural network algorithms with convolution techniques, and this algorithm is often used for digital image data (Diyasa et al. 2021). CNN consists of several main layers, namely Convolutional Layer that extracts features using filters, Activation Function (ReLU) that increases non-linearity, Pooling Layer that reduces the dimensionality of the data, Fully Connected Layer that performs classification, and Output Layer that uses softmax or sigmoid functions according to the type of classification (Goodfellow, Bengio, and Courville 2016).

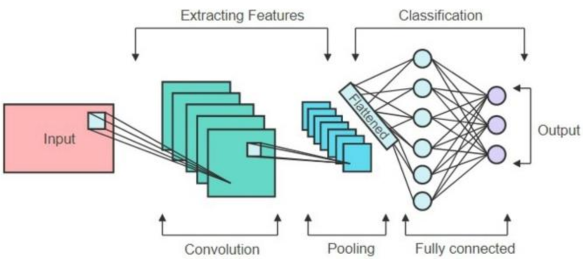

Figure 3. Summary of CNN Model

Fuzzy Inference System

Fuzzy Inference System (FIS) is a computational framework based on the concepts of fuzzy set theory, fuzzy IF-THEN rules, and fuzzy logic reasoning (Athiyah et al. 2021). The fuzzy inference process is generally depicted in the form of an architectural block diagram. It can be seen in image.

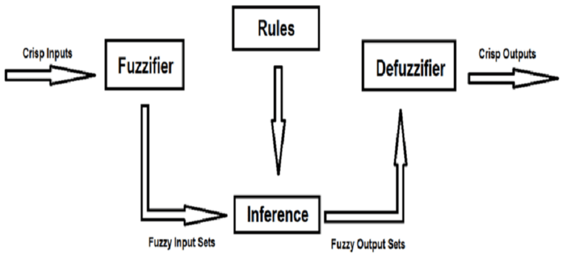

Figure 4. Summary of FIS Model

Fuzzy logic is usually used in problems related to elements of uncertainty, imprecision, noisy and so on (Destiawan, Arman Prasetya, and Ansori 2018). This system accepts input in the form of crisp values. The input is then processed in a database containing a series of fuzzy rules in the form of IF-THEN The process of converting fuzzy input into fuzzy output by fuzzifying each rule that has been formed in the previous stage (Kristanaya 2024).

Fuzzy Inference System consists of several processes involving several things such as membership functions, fuzzy logic operators and If-Then rules. A Fuzzy Inference System consists of three main components namely Fuzzifier, Inference Engine and Defuzzifier (Jumadi and Sartika 2020).

Procedure

This research procedure includes several stages, first data collection. Using a camera sampling technique to collect 100 images of rice leaf images from farmland. After the data is successfully obtained, data pre-processing is carried out by removing missing values, normalizing images, resizing images and image augmentation. This process is done using the TensorFlow or Keras library in the Python programming language. After the data is cleaned, model training is performed by applying CNN and CVNN models to train the rice leaf image classification model based on data that has been processed and labeled. Furthermore, the training of the 2 models is carried out to compare the accuracy between convolutional neural network and complex neural networks. Next, the model performance is evaluated using a classification report that includes accuracy, precision, recall, and F1-score metrics to assess how effective the model is in classifying rice leaf images. In the final stage, a Fuzzy Inference System (FIS) model is applied to predict disease severity based on visual features extracted from the leaf images.

Data Collection

In this study, the data used was obtained from www.kaggle.com. The dataset contains images of rice leaves used as a classification process that are infected with various types of diseases to be classified in this study including: Bacterial leaf blight, Brown spot, Leaf blast, and Healthy leaf. The amount of data obtained in this study was 8,501 images of rice leaf diseases. Rice leaf data using .JPG format.

RESULTS AND DISCUSSION

This research uses data obtained from Kaggle website, which consists of 8,501 JPG images. This dataset has been systematically divided into four main folders, each representing one disease class, namely Bacterial Leaf Blight, Brown Spot, Leaf Blast, and Healthy Leaf. The following is an example of the data used:

Table 1. Sample Data

No	Class Name	Rice Leaves	Qty
1.	Bacterial leaf blight		2.709
2.	Brown spot		3.014

3.	Leaf Blast		1.162
4.	Health y		1.616

The Complex-Valued Neural Network (CVNN) method was chosen to ensure that the dataset used is representative enough in quality and quantity to reflect real conditions more accurately. The labeling process is done automatically based on the folder name where the images are stored. For example, all images in the "Brown Spot" folder were labeled as class 1, "Bacterial Leaf Blight" as class 0, "Leaf Blast" as class 2, and "Healthy Leaf" as class 3. The labels are then converted into numeric format or one-hot encoding so that they can be used as classification targets in CNN and CVNN models.

After the labeling process is complete, the image data undergoes a preprocessing stage such as resizing, pixel normalization, and data augmentation to increase the variety and quality of training data. Next, the dataset is divided into two main subsets, namely training data and testing data with a proportion of 80% for training data and 20% for testing data. This division was done using the hold-out validation technique to reduce the biasing effect of a one-time data division.

Before being incorporated into the model, all rice leaf images were converted to a uniform size of 150 x 150 pixels, as per common standards in digital image processing. In the training process, experiments were conducted with varying the number of epochs from 10, 30, 50, to 100, to evaluate the effect of iteration length on model performance. The batch size was set at 32, meaning that the model processes 32 samples at once in each iteration, making the training process more computationally efficient.

Each class has variations in severity, lighting, shooting angle, and leaf orientation, which poses a challenge for the model to still be able to recognize patterns well and show strong generalization ability when tested under field conditions.

In addition, the training duration of each model was also recorded, including the execution time of 15 minutes per model, to assess computational efficiency as one of the important parameters in the evaluation of the overall system performance. The training and evaluation results were then used as the basis for comparing the performance of CVNN and CNN, as well as testing the potential integration of CVNN with Fuzzy Inference System (FIS) in the automatic and comprehensive diagnosis of rice leaf diseases.

Model: "sequential_4"

Layer (type)	Output Shape	Param #
complex_conv2d_3 (ComplexConv2D)	(None, 148, 148, 32)	2,368
complex_max_pooling2d_3 (ComplexMaxPooling2D)	(None, 74, 74, 32)	0
complex_conv2d_4 (ComplexConv2D)	(None, 72, 72, 64)	36,992
complex_max_pooling2d_4 (ComplexMaxPooling2D)	(None, 36, 36, 64)	0
complex_conv2d_5 (ComplexConv2D)	(None, 34, 34, 128)	147,712
complex_max_pooling2d_5 (ComplexMaxPooling2D)	(None, 17, 17, 128)	0
flatten_6 (Flatten)	(None, 36992)	0
dense_12 (Dense)	(None, 512)	18,940,416
dropout_3 (Dropout)	(None, 512)	0
dense_13 (Dense)	(None, 4)	2,052

Total params: 19,129,540 (72.97 MB)
Trainable params: 19,129,540 (72.97 MB)
Non-trainable params: 0 (0.00 B)

Figure 5. Detail about of CVNN Model

The Complex-Valued Neural Network (CVNN) model used in this research is a neural network arranged sequentially, where each layer is interconnected to process the image gradually. This architecture begins with the ComplexConv2D layer which has 32 filters of size (3x3) and uses the ReLU activation function, with an input image of 150x150 pixels and 3 color channels (RGB). Next, ComplexMaxPooling2D serves to reduce the image dimension through a 2x2 window. This process is followed by several additional complex convolution and pooling layers, with an increasing number of filters. The results are flattened through the Flatten layer and passed to the ComplexDense layer which contains 512 neurons with ReLU activation. The model has outperformed and convolutional layers with the addition of pooling and dropout layers (Riyantoko, Sugiarto, and Hindrayani 2021). Dropout is also used to prevent overfitting (Acarya, Muhaimin, and Hindrayani 2024), and finally the model produces a classification output through the ComplexDense layer with 4 softmax-activated neurons, each representing one of the four rice leaf disease classes.

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Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
flatten (Flatten)	(None, 36992)	0
dense (Dense)	(None, 128)	4,735,104
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 32)	2,080
dropout (Dropout)	(None, 32)	0
dense_3 (Dense)	(None, 4)	132

Total params: 4,838,820 (18.46 MB)
Trainable params: 4,838,820 (18.46 MB)
Non-trainable params: 0 (0.00 B)

Figure 6. Detail about of CNN Model

The Convolutional Neural Network (CNN) model employed in this study is composed of several sequential layers designed to effectively process and classify image data. It begins with a Conv2D layer that applies 32 filters with a kernel size of (3x3) and uses the ReLU activation function to extract important features from the input images. This is followed by a MaxPooling2D layer, which reduces the spatial dimensions of the feature maps by selecting the maximum value within a 2x2 window, thereby helping to minimize computational load and preserve essential information. The process continues with additional Conv2D and MaxPooling2D layers, each with increasingly complex filters to capture deeper patterns within the data. Once the final convolutional features are extracted, they are flattened into a single-dimensional vector using the Flatten layer to prepare the data for classification. This vector is then passed through a Dense layer consisting of 512 neurons and ReLU activation, which processes the extracted features. The network concludes with a final Dense layer containing 4 neurons and a softmax activation function, which generates classification outputs by providing the probability of the input image belonging to each of the four predefined classes.

Based on the experimental results, the accuracy value of the Complex-Valued Neural Network (CVNN) model is obtained. The table below presents a comparison of the accuracy levels achieved by the CVNN model in various test scenarios.

Figure 7. Plot of CNN Model

Figure 7 displays the evaluation graph of the Convolutional Neural Network (CNN) model used in this study. The graph shows the changes in accuracy and loss values during the training and validation process when the model was optimized using the Adam algorithm with a total of 100 epochs. Through this visualization, it can be clearly seen how the performance of the model evolves over the training time, both in terms of increasing accuracy and decreasing loss. The information presented by this graph is very useful for assessing the stability and effectiveness of the model training process in recognizing patterns in rice leaf disease image data.

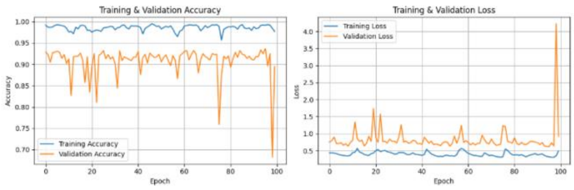

Figure 8. Plot of CVNN Model

Figure 8 presents the evaluation graph of the Complex-Valued Neural Network (CNN) model optimized with the Adam approach but only run for 50 epochs. This graph also displays the trend of accuracy and loss values at the training and validation stages, which can be used to compare the performance between CNN and CVNN. By presenting the two evaluation graphs, the reader can understand how different training structures and parameters affect the effectiveness of each model. This visualization also helps in further analyzing the advantages and limitations of each architecture in the context of plant disease image classification.

	precision	recall	f1-score	support
Bacterial leaf blight	0.92	0.93	0.92	542
Brown spot	0.95	0.92	0.94	603
Healthy Rice Leaf	0.95	0.96	0.96	233
Leaf blast	0.87	0.88	0.87	324
accuracy			0.92	1702
macro avg	0.92	0.92	0.92	1702
weighted avg	0.92	0.92	0.92	1702

Figure 9. Classification report of CVNN model

Based on the evaluation results, the CVNN model showed excellent performance with an overall accuracy of 92%. Each class had high precision, recall, and F1-score values, with Healthy Rice Leaf recording the highest score (F1-score 0.96), followed by Brown Spot (0.94), Bacterial Leaf Blight (0.92), and Leaf Blast (0.87). The macro average and weighted average scores for all metrics were also consistent at 0.92, indicating a balanced ability of the model to recognize all four classes of rice leaf diseases. These results show that the CVNN model has strong generalization ability and is feasible to be used to support the process of diagnosing diseases in rice plants.

	precision	recall	f1-score	support
Bacterial leaf blight	0.92	0.92	0.92	542
Brown spot	0.90	0.89	0.89	603
Healthy Rice Leaf	0.96	0.79	0.87	233
Leaf blast	0.79	0.91	0.84	324
accuracy			0.89	1702
macro avg	0.89	0.88	0.88	1702
weighted avg	0.89	0.89	0.89	1702

Figure 10. Classification report of CNN model

The figure shows, based on the evaluation results of the displayed CNN model, the overall accuracy of the model reached 89%, showing a good ability to recognize four classes of rice leaf diseases. The model displayed high performance in the Bacterial leaf blight and Brown spot classes, with precision, recall, and F1-score above 0.90. However, there was an imbalance in the Healthy Rice Leaf class, which had perfect precision (0.96) but lower recall (0.79), and Leaf blast class, which had high recall (0.91) but lower precision (0.79). In general, the CNN model shows quite good results, although it still requires improvement in generalization ability for some classes to make predictions more balanced and accurate.

Figure 9. Acuracy of FIS Model

The figure shows based on the Fuzzy Inference System (FIS) model, the prediction of the severity of rice leaf blast was successful by dividing the results into three categories, namely Light, Medium, and High. In the Leaf Blast class from a total of 1,616 images, 54.6% were categorized in High severity, indicating significant damage to the leaves. For the Brown Spot class of 2,734 images, most or about 72.7% were in the Moderate category, while only a few were classified as High, which was about 2.9%. Meanwhile, in the Bacterial Leaf Blight class out of a total of 2,703 images, more than 70% were at Moderate severity, with about 23.1% falling into the High category. These results show that the FIS model is able to categorize disease severity based on visual leaf characteristics proportionally, although the distribution of each class varies, and can be used as a basis for providing appropriate treatment recommendations for farmers.

CONCLUSIONS AND SUGGESTIONS

Conclusion

Based on the evaluation results of CVNN, CNN, and FIS models in diagnosing rice leaf diseases, it can be concluded that the CVNN model shows superior performance compared to the Convolutional Neural Network (CNN) model in classifying rice leaf disease images. The CVNN model produces 92% accuracy, where all classes produce high and balanced precision, recall, and F1-score values. While the CNN model also provides satisfactory results with an accuracy of 89%, although there are still imbalances in some classes. Meanwhile, the FIS model successfully performed the disease severity into three categories, namely Mild, Medium, and High, according to the visual characteristics of each disease class. The severity of the rice leaf disease image of the most high category in the leaf blast class is the highest of all classes. The combination of the high classification capability of CVNN and severity analysis using FIS proves that this hybrid approach is effective to support automatic and comprehensive diagnosis of rice leaf diseases, which can help farmers make early and informed decisions.

Suggestion

Future research is recommended to develop a hybrid approach between CNN or CVNN with Fuzzy Inference System (FIS) to improve classification accuracy as well as the interpretability of prediction results. Hyperparameter adjustments such as number of epochs, batch size, and learning rate need to be optimized for better results. Data variation and augmentation are also important to make the model more adaptive to real conditions. In addition, direct application of the model in the field and improved interpretability through visualization methods such as Grad-CAM can help users understand the prediction results. Finally, the integration of FIS-based decision-making systems can provide more practical and applicable action recommendations for users, especially in agriculture.

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