Automatic diagnosis of rice plant diseases using VGG-16 and computer vision

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ABSTRACT

Pathogens are organisms that cause disease in plants. In the case of rice, these pathogens can include fungi, bacteria, nematodes, protozoa, and viruses. This study aims to investigate rice plant diseases using a hybrid system that employs the visual geometry group-16 (VGG-16) architecture and computer vision techniques, alongside various optimization algorithms and hyperparameters. We utilize the convolutional neural network (CNN) architecture of VGG-16 for feature extraction, implementing a process known as transfer learning. Additionally, this research compares different optimization algorithms with the VGG-16 model to identify the most effective optimization for the CNN architecture applied to the tested dataset. The main contribution of this study is the development of a model for identifying rice plant diseases based on data collected using VGG-16 for feature extraction and neural networks for classification with specific parameters. Our findings indicate that the best optimization algorithm is stochastic gradient descent (SGD) with momentum, achieving training and validation loss results of 0.173 and 0.168, respectively. Furthermore, the training and validation accuracies were 0.95 and 0.957. The model's performance metrics include an accuracy of 95.75, precision of 95.75, recall of 95.75, and an F1-score of 95.73.

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1. INTRODUCTION

Indonesia is an agricultural country where a significant portion of the population works in the farming sector. In an agrarian society, agriculture plays a crucial role in various areas, including basic needs, the economy, community well-being, and trade [1]. The success of agriculture largely depends on the harvest, which can be jeopardized by pests and diseases [2]. Understanding plant diseases is essential to prevent infections that could lead to crop failure. Therefore, technology is employed to identify types of diseases in plants, allowing for appropriate treatments to be applied based on specific issues. One efficient approach to discern Phyto pathological conditions is via supervised machine learning techniques, notably deep learning, which is regarded as preeminent owing to its capacity to proficiently extract salient features from visual data [3]-[5]. A prominent architecture within deep learning for image analysis is the convolutional neural network (CNN) [6].

In the forward propagation process, several hyperparameters play a crucial role across all layers, including the activation function, learning rate, batch size, and optimizer. The output weights are iteratively modified during the backpropagation phase for improved outcome [7]. Optimization methods are employed to modify the weights and to address overfitting, which is a common challenge in neural networks [8]. Numerous optimization algorithms can effectively adjust the weights, allowing the neural network model to perform optimally [9].

Research on the classification of rice plant diseases has been extensively conducted using various methods, with CNN being one of the most widely used approaches. In addition to traditional CNNs, recent studies have been exploring transfer learning, which involves adopting pre-trained models and applying them to new cases. Some of the commonly used transfer learning architectures include visual geometry group-16 (VGG-16), AlexNet, Inception, residual network (ResNet), and densely connected convolutional network (DenseNet) [10]. Furthermore, research in rice plant disease classification is evolving by optimizing processes to enhance results, focusing on selecting optimal methods for specific datasets. Techniques such as ensemble methods are also being utilized [11]. Commonly compared optimization algorithms include stochastic gradient descent (SGD), SGD with momentum, Nesterov momentum, AdaDelta, AdaGrad, adaptive moment estimation (Adam), and RMSprop.

While previous studies show promise, a notable gap exists in evaluating optimization algorithms on the VGG-16 architecture for rice disease classification. Despite VGG-16's popularity, comprehensive comparative analysis on optimizer effects remains insufficient, especially regarding modifications from this research. This study aims to address this gap by examining the efficacy of various optimizers like SGD with momentum, Adam, and RMSprop on a VGG-16 model specific to a rice leaf disease dataset. Through direct comparison, the research seeks to determine the optimal optimizer for enhanced accuracy and efficiency in agricultural applications.

This study assesses a hybrid system employing the VGG-16 architecture for classifying rice plant diseases. It seeks to conduct a comparative analysis of diverse optimization algorithms and hyperparameters, with results represented through linear diagrams and tables for enhanced performance evaluation. The research employs Python in conjunction with the TensorFlow framework to evaluate the effectiveness of VGG-16 alongside various optimization algorithms.

2. METHOD

The dataset used in this study was compiled from five publicly available sources of rice plant disease images, each providing different classes, resolutions, and sample distributions [12]–[16]. All datasets were merged into a unified collection to ensure consistency during model development. The combined dataset was then reformatted to achieve a uniform directory structure and labeling scheme.

After merging, a series of pre-processing stages was applied to standardize image characteristics and improve data quality. The pre-processing steps included resizing, cropping, contrast enhancement, and color normalization to accelerate model convergence and reduce computational complexity [17]–[23]. These operations were implemented to ensure that all images had consistent dimensions and were suitable for training a deep learning model.

CNNs have been widely employed in image classification tasks because of their ability to extract hierarchical feature representations [24]–[27]. Prior research has demonstrated the effectiveness of CNN-based techniques across various computer vision problems, ranging from generative image modeling to medical image analysis [28]–[31]. These findings provide strong support for adopting CNN architectures in agricultural disease classification. In this study, the CNN framework was implemented using the VGG-16 architecture, which has been recognized for its stable structure and capability to capture fine-grained visual patterns through its deep, sequential convolutional layers [32], [33].

The VGG-16 model consists of 13 convolutional layers and three fully connected layers, operating with uniform 3×3 filters throughout its architecture. To adapt VGG-16 for the rice disease dataset, transfer learning was employed by initializing the model with pre-trained ImageNet weights. The convolutional layers were used as fixed feature extractors, and the original fully connected layers were replaced with a custom classifier tailored to the number of classes in this study. Various optimization algorithms were evaluated to determine the most effective configuration for the modified VGG-16 model [34]–[46].

The dataset was divided into training, validation, and testing subsets following recommended practices for achieving reliable model generalization. The training set was used to optimize model parameters, the validation set monitored performance during training, and the testing set assessed final model quality. The model was trained using categorical cross-entropy as the loss function and accuracy as the primary evaluation metric [47]–[49]. Performance assessments also utilized additional metrics accuracy, precision, recall, and F1-score which provide a more comprehensive evaluation of classification effectiveness [50], [51]. A detailed depiction of the research workflow is presented in Figure 1.

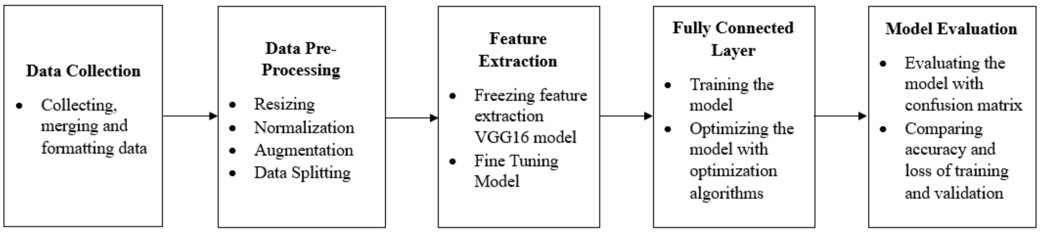

Figure 1. Research process diagram

True positives (TP) refer to the number of positive images that are correctly predicted, while false negatives (FN) are the positive images that are misclassified. False positives (FP) indicate the number of negative images that are incorrectly predicted as positive, and true negatives (TN) represent the number of negative images that are correctly identified [52], [53]. The entire research process is shown in Figure 1.

Figure 1 illustrates the research workflow, initiating with data collection from various sources, followed by pre-processing for consistency and quality. The data is divided into training, validation, and test sets to facilitate effective model development and evaluation. In the modeling phase, a modified VGG-16 architecture is employed for feature extraction via transfer learning. The extracted features are then fed into a newly developed FC layer for classification, utilizing multiple optimization algorithms for training. Finally, the effectiveness of the trained model is rigorously evaluated using standard metrics such as accuracy, precision, recall, and F1-score to determine the optimal configuration.

3. RESULTS AND DISCUSSION

3.1. The proposed model

The model employed in this study is fine-tuning, as illustrated in Figure 1. It consists of a total of 14,714,688 parameters, including both trainable and non-trainable parameters. This approach involves freezing some parameters while adjusting others to fit the data, a process referred to as fine-tuning the VGG-16 model [32], [33]. Fine-tuning the VGG-16 model in the code above uses a loop to explicitly freeze the first 15 layers and allow the rest to be trained is shown in Table 1.

Table 1. Comparison of VGG-16, fine-tuning VGG-16 and FC layer

Parameters	VGG-16	Fine-tuning VGG-16	FC layer
Total params	14.714.688	14.714.688	14.843.594
Trainable params	14.714.688	0	128.650
Non-trainable params	0	14.714.688	14.714.994

FC layer [28], [47] in this study is different from the VGG-16 model, due to the difference in the amount of data and classification objects, the comparison of parameters used in this study with VGG16 is shown in Table 2. This research model modifies the VGG-16 architecture, specifically its FC layer. Our model features two layers instead of three, with fewer neurons (128 and 64) as detailed in Table 2. Moreover, it employs dropout layers, batch normalization, and L2 regularization to mitigate overfitting and improve stability, unlike the standard VGG-16 architecture.

Table 2. Comparison of VGG-16 model and research model

Aspect	VGG-16 model	Research model
Number of FC layers	3	2
Number of first FC layer neurons	4096	128
Dropout	There is none	There is, with a rate of 0.6
Batch normalization	There isn’t any	Yes
Regularization	There isn’t any	Yes, with L2 regularization and a factor of 0.01

The modifications to VGG-16 balance complexity and performance. The reduction of layers and neurons decreased trainable parameters significantly. This reduction improves computational efficiency, speeds up training, and reduces overfitting. Despite its simplification, the model maintains strong accuracy and performance, demonstrating that less complexity can effectively address certain classification tasks.

3.2. Training in model

The model to be trained in this study uses several parameters in model compilation, including optimization, learning rate, loss function and evaluation metrics. The model training uses different parameters from the original VGG-16 model with the goal of adapting to graphics processing unit (GPU) memory, accelerating model training, maintaining training stability and improving model. The training process is given a limitation, if the validation loss does not increase for 5 epochs, then the training will be stopped with the goal of efficient training time. A comparison between the training parameters on the research model and the VGG-16 model can be seen in Table 3.

Table 3. Comparison of VGG-16 training and research model

Feature	Model VGG-16	Research model
Early stopping	No	Yes
Optimizer	SGD	Adam
Learning rate	0.001	0.001
Loss function	Categorical crossentropy	Categorical crossentropy
Metric	Accuracy, top 5 accuracy	Accuracy
Batch size	64	8
Epochs	100	30

3.3. Model evaluation

3.3.1. Adam and Adamax

The model with Adam's optimization algorithm [34] sees the performance of the model through the classification report with a classification result accuracy of 0.95 generally indicating good performance. Furthermore, evaluating the original classification report model with confusion matrix on 10 classes with the comparison results of precision, recall and F1-score metrics shown in Figure 2. Testing the reliability of the model is done with another dataset of this model that has been saved with the name "model_rice_disease_adam_lr.h5" with tungro disease data [16] with a result of 99.9%.

The model with Adamax's optimization algorithm sees the performance of the model through the classification report with a classification result accuracy of 0.95 generally indicating good performance [34]. Furthermore, evaluating the original classification report model with confusion matrix on 10 classes with the comparison results of precision, recall and F1-score metrics shown in Figure 3. Testing the reliability of the model is done with another dataset of this model that has been saved with the name "model_rice_disease_adamax_lr.h5" with tungro disease data [16] with a result of 99.9%.

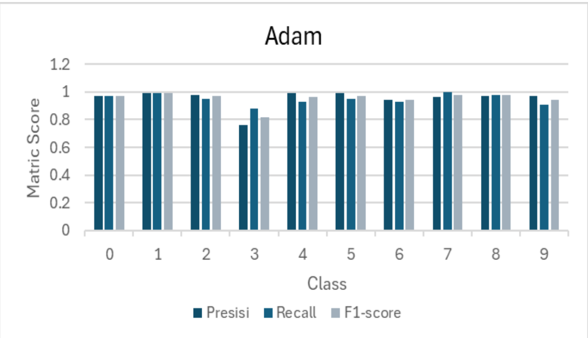

Figure 2. Adam model training

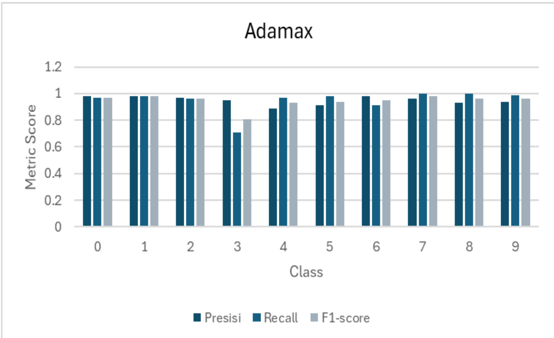

Figure 3. Adamax model training

3.3.2. AdaGrad and AdaDelta

The model with AdaGrad's optimization algorithm [35] sees the performance of the model through the classification report with a classification result accuracy of 0.95 generally indicating good performance. Furthermore, evaluating the original classification report model with confusion matrix on 10 classes with the comparison results of precision, recall and F1-score metrics shown in Figure 4. Testing the reliability of the model is done with another dataset of this model that has been saved with the name “model_rice_disease_adagrad_lr.h5” with tungro disease data [16] with a result of 99.878%.

The model with Adadelta’s optimization algorithm [35] shows a classification accuracy of 0.73 which generally indicates that the model has poor performance in each class caused by the optimization algorithm used, especially in class 3 with precision, recall and F1-score classification scores of 0.43, 0.44 and 0.43 which indicate that the model has difficulty training and classifying class 3. Furthermore, evaluating the original classification report model with confusion matrix on 10 classes with the comparison results of precision, recall and F1-score metrics shown in Figure 5. Testing the reliability of the model is done with another dataset of this model that has been saved with the name “model_rice_disease_adadelta_lr.h5” with tungro disease data [16] with a result of 87.11%.

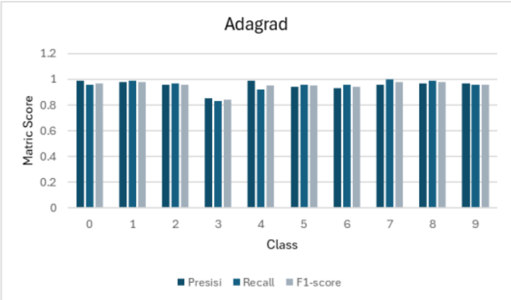

Figure 4. AdaGrad model training

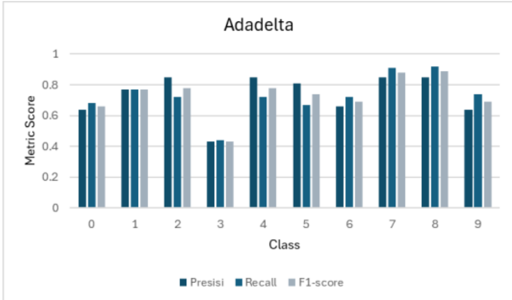

Figure 5. AdaDelta model training

3.3.3. RMSprop and stochastic gradient descent

A model with the SGD with Momentum optimization algorithm that shows a classification result accuracy of 0.96 which generally indicates that the model has good performance. Furthermore, evaluating the original classification report model with confusion matrix on 10 classes with the comparison results of Precision, Recall and F1-score metrics shown in Figure 6. Testing the reliability of the model is done with another dataset of this model that has been saved with the name “model_rice_disease_SGD_Momentum_lr.h5” with tungro disease data [16] with a result of 99.99997%.

A model with the SGD optimization algorithm that shows a classification result accuracy of 0.95 which generally indicates that the model has good performance. Furthermore, evaluating the original classification report model with confusion matrix on 10 classes with the comparison results of Precision, Recall and F1-score metrics shown in Figure 7. Testing the reliability of the model is done with another dataset of this model that has been saved with the name “model_rice_disease_SGD_lr.h5” with tungro disease data [16] with a result of 99.988%.

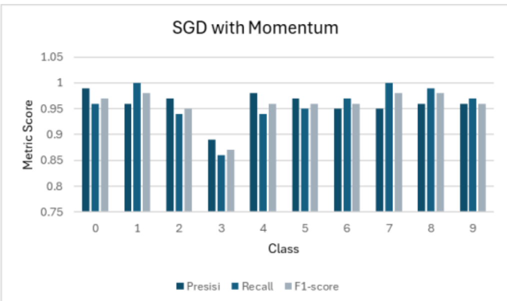

Figure 6. SGD with momentum model training

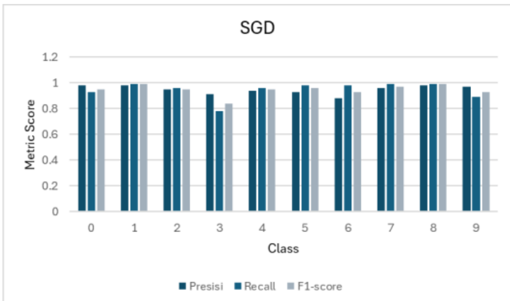

Figure 7. SDG model training

3.3.4. SGD with momentum

The model with the RMSprop optimization algorithm has a classification result accuracy of 0.93 which generally indicates that the model has good performance. Furthermore, evaluating the original classification report model with confusion matrix on 10 classes with the comparison results of precision, recall and F1-score metrics shown in Figure 8. Testing the reliability of the model is done with another dataset of this model that has been saved with the name "model_rice_disease_RMSProp_lr.h5" with tungro disease data [16] with a result of 99.878%.

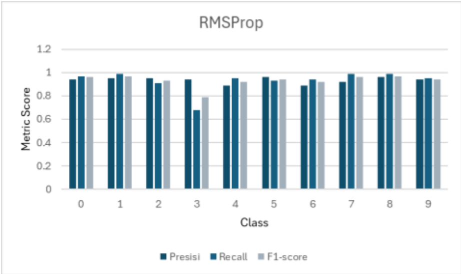

Figure 8. RMSProp model training

3.4. Comparison of optimization algorithm results

This first comparison evaluation compares the loss and accuracy of all optimization algorithms at the 30th epoch and the curve results of each optimization algorithm. The comparison of loss and accuracy of optimization algorithms at the 30th epochs are shown in Table 4. Table 4 shows that the best optimization algorithm is SGD with momentum with training and validation loss values of 0.173 and 0.168, training and validation accuracy of 0.95 and 0.957. In addition, SGD with momentum has the best loss and accuracy curves with stable curves and minimal ripples that show small model overfitting as shown in Figure 9. The worst optimization algorithm is AdaDelta with training and validation loss values of 2.7 and 2.35, training and validation accuracy of 0.6 and 0.73.

Table 4. Comparison of accuracy, precision, recall and F1-score

Model	Loss training	Loss validation	Accuracy training	Accuracy validation	Epochs to
Adam	0.175	0.2	0.953	0.95	30
Adamax	0.155	0.23	0.958	0.947	30
AdaGrad	0.7	0.68	0.941	0.952	30
AdaDelta	2.7	2.35	0.6	0.73	30
RMSprop	0.294	0.294	0.916	0.93	30
SGD	0.55	0.57	0.951	0.947	30
SGD with momentum	0.173	0.168	0.95	0.957	30

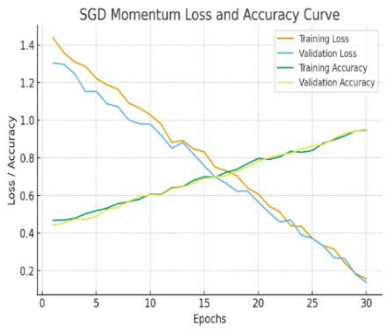

Figure 9. SGD momentum loss and accuracy curve

Overcoming overfitting is essential in deep learning model development. This research employed regularization techniques, including dropout, batch normalization, and L2 regularization. The approach demonstrated efficacy, evidenced by stable training and validation curves, particularly with the momentum-enabled SGD optimizer. The minimal divergence in accuracy curves suggests that the model preserves strong generalization capabilities. This second comparison evaluation compares the accuracy, precision, recall and F1-score of the tested optimization algorithms as in Table 5.

Table 5. Comparison of accuracy, precision, recall and F1-score

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Adam	95	95.32	95	95.09
Adamax	94.71	94.83	94.71	94.56
AdaGrad	95.29	95.3	95.29	95.27
AdaDelta	71.57	71.95	71.57	71.56
RMSprop	93.18	93.25	93.18	92.98
SGD	94.79	94.85	94.79	94.71
SGD with momentum	95.75	95.75	95.75	95.73

In Table 5 the model with the highest accuracy, precision, recall and F1-score [51] namely 95.75, 95.75, 95.75 and 95.73 is SGD with momentum with momentum of 0.8 and Nesterov = false and the model with the worst accuracy, precision, recall and F1-score namely 71.57, 71.95, 71.57 and 71.56 is adadelta, these results show that the latest models such as Adam and Adamax are not necessarily the best for every classification case.

3.5. Model testing using smartphone

The model was tested on an Android smartphone to validate its real-world prediction accuracy. It achieved 100% accuracy in detecting rice blast disease, confirming its practical reliability. The app also supports real-time image capture via the phone's camera not just pre-loaded images as shown in Figure 10, making it more user-friendly for field deployment.

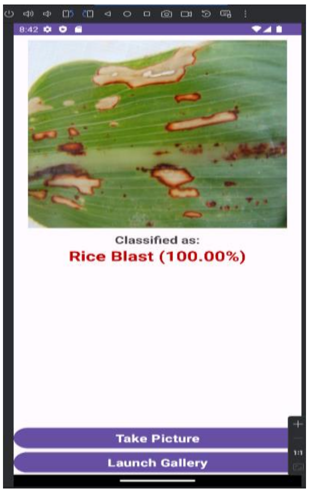

Figure 10. Model testing with smartphone

4. CONCLUSION

This study developed a deep learning model for rice plant disease identification using the VGG-16 architecture for feature extraction and a customized neural network for classification. The research identified SGD with momentum as the most effective optimization algorithm, achieving training and validation losses of 0.173 and 0.168, and accuracy of 95% and 95.7%, respectively. The model demonstrated high overall performance, with accuracy, precision, recall, and F1-score all approximating 95.75%. The utilization of VGG-16 as a feature extractor was significantly effective, allowing the model to leverage pre-trained weights that were fine-tuned for optimal results on the dataset. The optimal integration of the modified FC layer and the SGD with momentum algorithm yielded a remarkable test accuracy of 99.99% on new data, outperforming other optimizers such as Adam and Adamax.

Building upon these findings, future research avenues merit exploration. Investigating modifications to the neural network architecture, including additional FC layers or increased neuron counts, may reveal more complex patterns. A systematic study on hyperparameter tuning, emphasizing the optimization of learning rate, dropout rates, and regularization values, is essential for enhanced performance. Comparative analysis of our VGG-16-based model with other leading transfer learning architectures, such as ResNet or DenseNet, is recommended to identify the most effective classification approach. Lastly, exploring larger and more diverse datasets could improve the model's generalization capabilities, ensuring reliability in practical agricultural applications.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Henderi	✓	✓				✓		✓	✓	✓	✓	✓		
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Muhammad Hudzaifah Nasrullah	✓		✓	✓			✓			✓	✓		✓	✓
Didik Setiyadi Azizah	✓	✓				✓		✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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