CNN Optimization with Adam Optimizer for Mushroom Data Classification

Dika, Zulham Sitorus

Abstract

Mushroom identification is an important task in food safety and biological classification due to the morphological similarities between edible and poisonous species. Traditional identification methods often rely on expert knowledge and manual observation, which may be time-consuming and prone to human error. Therefore, this study proposes an optimized Convolutional Neural Network (CNN) model using Adam Optimizer for mushroom classification. The proposed approach employs image preprocessing techniques including resizing, normalization, and data augmentation to improve data quality and model robustness. The dataset was divided into training, validation, and testing subsets to ensure reliable model evaluation. CNN architecture consisting of convolutional, pooling, and fully connected layers was implemented and trained using Adam Optimizer with adaptive learning rate mechanisms. Experimental results demonstrated that the proposed model achieved high classification performance, with training accuracy reaching 98.21% and validation accuracy of 96.54%, accompanied by consistently decreasing loss values. Confusion matrix analysis further confirmed reliable classification capability with minimal misclassification between mushroom classes. Comparative evaluation indicated that Adam Optimizer outperformed conventional optimization methods in terms of convergence speed and classification accuracy. These findings suggest that CNN optimized with Adam provides an effective and reliable framework for automated mushroom classification and has strong potential for applications in food safety, agriculture, and intelligent biological image recognition systems.

Keywords*:* Convolutional Neural Network, Adam Optimizer, Mushroom Classification, Deep Learning, Image Classification, Computer Vision

Dika[1]
[1]Information Technology, Universitas Pembangunan Panca Budi, Indonesia
e-mail: tiepie71@gmail.com[1]

Zulham Sitorus[2]
[2]Information Technology, Universitas Pembangunan Panca Budi, Indonesia
e-mail: zulhamsitorus@gmail.com[2]

Introduction

Mushrooms represent an important biological resource with significant economic, nutritional, and medicinal value. Various mushroom species are widely consumed as food and utilized in pharmaceutical and agricultural industries. However, the existence of poisonous mushroom species that visually resemble edible mushrooms poses a serious challenge in identification and classification processes. Misidentification may lead to severe health consequences, including food poisoning and even fatal incidents. Therefore, an accurate and reliable mushroom classification system is essential to support safe consumption and improve identification efficiency.

Traditional mushroom identification methods generally rely on expert knowledge and manual observation of morphological characteristics such as color, texture, cap shape, and gill structure. Although effective in certain conditions, manual identification often requires extensive expertise and considerable time. In addition, environmental factors, image quality, and morphological similarities among mushroom species may reduce classification accuracy and increase the possibility of human error.

Recent advances in artificial intelligence, particularly deep learning, have provided promising solutions for image classification problems. Among various deep learning approaches, Convolutional Neural Network (CNN) has demonstrated superior capability in automatically extracting hierarchical features from image data. CNN eliminates the need for handcrafted feature extraction and has achieved remarkable performance across numerous computer vision applications, including medical imaging, agriculture, and object recognition. Due to its capability to learn spatial patterns directly from images, CNN has become an effective approach for biological image classification tasks, including mushroom recognition.

Despite the effectiveness of CNN, model performance is highly influenced by the optimization algorithm employed during training. The optimizer determines how network parameters are updated to minimize prediction errors and directly affects convergence speed, training stability, and final classification performance. Conventional optimizers such as Stochastic Gradient Descent (SGD) may suffer from slow convergence and sensitivity to learning rate settings. Consequently, selecting an appropriate optimization technique becomes a crucial factor in improving CNN performance.

Adam (Adaptive Moment Estimation) Optimizer has emerged as one of the most widely used optimization algorithms in deep learning due to its ability to adaptively adjust learning rates based on first and second moment estimations of gradients. Adam combines the advantages of momentum and adaptive learning rate strategies, enabling faster convergence and more stable training compared to several conventional methods. Previous studies have reported that Adam frequently produces better classification accuracy while reducing training complexity in image-based classification problems.

Several studies have investigated mushroom classification using machine learning and deep learning approaches. However, many existing works primarily focus on CNN implementation without comprehensive analysis of optimization strategies or provide limited evaluation regarding training behavior and classification performance. This limitation indicates the need for further investigation into the contribution of optimization algorithms toward enhancing CNN-based mushroom classification.

Therefore, this study aims to optimize the performance of Convolutional Neural Network using Adam Optimizer for mushroom classification. The proposed approach evaluates the effectiveness of Adam in improving classification accuracy, minimizing loss values, and enhancing model generalization capability. Performance evaluation is conducted using accuracy, precision, recall, F1-score, and confusion matrix analysis. The findings of this study are expected to contribute to the development of intelligent mushroom identification systems and provide practical implications for food safety, agriculture, and biological image analysis applications.

Literature Review

2.1 Mushroom Classification

Mushroom classification has become an increasingly important research area due to its implications for food safety, agriculture, and biodiversity conservation. The identification of edible and poisonous mushrooms presents considerable challenges because many species exhibit highly similar morphological characteristics. Traditional identification methods generally depend on expert observation and taxonomic analysis, which are often time-consuming and susceptible to human error. Consequently, automated classification systems have attracted growing interest as an alternative approach for improving identification accuracy and efficiency.

Machine learning approaches have been widely applied to mushroom classification problems. Early studies employed conventional classification algorithms such as Decision Tree, Support Vector Machine (SVM), Naïve Bayes, and Random Forest. These methods demonstrated promising performance on structured datasets; however, their effectiveness strongly depended on manual feature engineering and expert-defined characteristics. As image-based datasets became increasingly available, deep learning techniques emerged as more suitable solutions due to their capability to automatically learn representative features directly from raw image data.

2.2 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning architecture specifically designed for image processing and pattern recognition tasks. CNN has achieved substantial success in various computer vision applications because of its ability to learn spatial hierarchies and extract complex image features automatically.

A typical CNN architecture consists of several main layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers function to detect local image features such as edges, textures, and shapes through learnable filters. Pooling layers reduce feature dimensionality while preserving essential information, thereby improving computational efficiency and reducing overfitting risk. Finally, fully connected layers perform the classification process based on extracted features.

Compared to traditional machine learning methods, CNN offers several advantages. First, CNN eliminates the dependency on handcrafted feature extraction. Second, hierarchical feature learning enables the model to capture both low-level and high-level image characteristics. These advantages make CNN highly effective for biological image classification tasks, including plant disease recognition, animal species identification, and mushroom classification.

Recent studies have reported that CNN models achieve high classification accuracy in image recognition problems. Nevertheless, CNN performance is strongly influenced by model architecture, dataset quality, and optimization algorithms employed during training.

2.3 Adam Optimizer

The optimization algorithm plays a critical role in CNN training because it determines how network weights are updated to minimize prediction error. Gradient-based optimization methods are commonly used in deep learning; however, conventional approaches such as Stochastic Gradient Descent (SGD) may encounter limitations including slow convergence and sensitivity to learning rate selection. Adam (Adaptive Moment Estimation) Optimizer was introduced to address these challenges by combining momentum and adaptive learning rate techniques. Adam estimates the first moment (mean) and second moment (variance) of gradients to update model parameters efficiently.

Research Methodology

3.1 Research Design

This study employs an experimental research design using a deep learning approach to classify mushroom images. The primary objective is to optimize the performance of Convolutional Neural Network (CNN) using Adam Optimizer and evaluate its effectiveness in distinguishing mushroom classes. The experimental design involves dataset preparation, image preprocessing, CNN model development, optimization using Adam, and performance evaluation. The overall research framework is illustrated through several sequential stages, beginning with data acquisition and ending with model evaluation and result analysis.

3.2 Dataset Collection

The dataset used in this study consists of mushroom image data categorized into multiple classes representing edible and poisonous mushrooms. The images were collected from publicly available datasets and prepared for supervised learning tasks.
The dataset was divided into three subsets:

Table 1 Dataset Type

Dataset Type	Percentage
Training Data	80%
Validation Data	10%
Testing Data	10%

The training dataset was used to train the CNN model, while validation data was employed to monitor model learning performance and prevent overfitting. The testing dataset was utilized to evaluate final model performance.

3.3 Image Preprocessing

Image preprocessing is a critical step to improve data quality and ensure consistency before training the CNN model. Several preprocessing techniques were applied.
1. Image Resizing
All mushroom images were resized to a fixed dimension of 224 × 224 pixels to ensure compatibility with CNN input requirements and reduce computational complexity.
2. Normalization
Pixel values were normalized to a range between 0 and 1 using the following equation:

$$X_{norm} = \frac{X}{255}$$

Normalization improves numerical stability and accelerates model convergence during training.
3. Data Augmentation
To increase dataset variability and reduce overfitting, several augmentation techniques were applied, including:

1. Rotation
2. Horizontal flipping
3. Zooming
4. Brightness adjustment

Data augmentation enables the CNN model to learn more robust and generalized image features.

3.4 CNN Architecture

The proposed classification model utilizes a Convolutional Neural Network architecture composed of convolutional, pooling, and fully connected layers.
The CNN architecture consists of:

Table 2 The CNN architecture

Layer	Configuration
Input Layer	224 × 224 × 3
Convolution Layer 1	32 filters, 3×3 kernel, ReLU
Max Pooling 1	2×2

Layer	Configuration
Convolution Layer 2	64 filters, 3×3 kernel, ReLU
Max Pooling 2	2×2
Convolution Layer 3	128 filters, 3×3 kernel, ReLU
Max Pooling 3	2×2
Flatten Layer	Feature transformation
Dense Layer	128 neurons, ReLU
Output Layer	Softmax

The Rectified Linear Unit (ReLU) activation function was applied to hidden layers to introduce non-linearity and improve feature learning. The Softmax activation function was used in the output layer to generate class probability distributions.

Results

4.1 Training and Validation Accuracy/Loss

CNN model trained using Adam Optimizer with a learning rate of 0.001 for 30 epochs. The dataset was divided 80 % of the training data and 20% of the validation data. The training process show improvement stable accuracy as well as decline loss value at each epoch.

Table 3 Training and Validation Performance

Epoch	Accuracy Training	Validation Accuracy	Training Loss	Validation Loss
5	82.14%	79.83%	0.462	0.521
10	89.37%	87.41%	0.298	0.341
15	93.26%	91.78%	0.201	0.254
20	95.41%	94.22%	0.141	0.183
25	97.12%	95.87%	0.093	0.131
30	98.21%	96.54%	0.062	0.104

Training results show that the training accuracy value increases from 82.14% in the 5th epoch to 98.21% in the 30th epoch. At the same time, validation accuracy also experienced improvement until reached 96.54%. The loss value in training and validation experienced decline in a way consistent, showing that the model is capable learn data patterns with Good.

Relative differences small between training accuracy and validation accuracy shows that the model has ability good and bad generalizations experiencing overfitting significant.

4.2 Confusion Matrix

Model evaluation is carried out using confusion matrix to know ability classification in each class mold.

Table 4 Confusion Matrix Results

Actual / Predicted	Edible	Poisonous
Edible	188	7
Poisonous	6	199

the confusion matrix obtained :

1. True Positive (TP) = 199
2. True Negative (TN) = 188
3. False Positive (FP) = 7
4. False Negative (FN) = 6

From these results counted metric evaluation as follows:

Table 5 Metric Evaluation

Metric	Value
Accuracy	96.75%

Metric	Value
Precision	96.60%
Recall	97.07%
F1-Score	96.83%

The accuracy value of 96.75% shows that part large mushroom data succeed classified with correct by CNN model.

4.3 Performance Comparison

For know effectiveness of Adam Optimizer, CNN performance compared with other optimizers.

Table 6 Optimizer Performance Comparison

Optimizer	Accuracy	Precision	Recall	F1-Score
SGD	90.82%	89.94%	91.15%	90.54%
RMSProp	94.37%	94.11%	94.62%	94.36%
Adam	96.75%	96.60%	97.07%	96.83%

Test results show that Adam Optimizer produces performance best compared to SGD and RMSProp. Improvement accuracy as big as around 5–6% compared to SGD shows Adam's ability in do learning rate adaptation automatic so that the convergence process become more fast and stable.

4.4 Result Analysis

Research result show that optimized use of CNN with Adam Optimizer able to increase performance fungal data classification in a way significant. Adam Optimizer provides stability during the training process as indicated by the increasing accuracy curve and decreasing loss in a way consistent.

Besides that, the confusion matrix shows amount error relative classification small. Error classification that is still happen possibility caused by visual similarities between type mushrooms, variations lighting, as well as quality image used in the dataset.

Compared to other optimizers, Adam shows superiority in terms of convergence speed and classification performance. This in accordance with Adam's characteristics combine momentum and adaptive learning rate so that capable avoiding local minima as well as speed up the optimization process.

In a way Overall, the CNN model with Adam Optimizer is proven to be effective For classification of fungal data and potential applied to the system identification mold based intelligence artificial in the field agriculture, food, and education.

Conclusion

This study investigated the optimization of Convolutional Neural Network (CNN) using Adam Optimizer for mushroom classification. The proposed approach demonstrated strong performance in distinguishing mushroom classes through automatic feature extraction and adaptive optimization mechanisms. The experimental results showed that the CNN model achieved high classification performance, as indicated by increasing training and validation accuracy as well as decreasing loss values throughout the training process.

The implementation of Adam Optimizer contributed significantly to model stability and convergence speed. Compared with conventional optimization methods, Adam provided better learning efficiency through adaptive learning rate adjustment and momentum-based parameter updates. The evaluation results, supported by confusion matrix analysis and performance metrics including accuracy, precision, recall, and F1-score, confirmed that the optimized CNN model was capable of classifying mushroom data with high reliability and minimal misclassification.

Furthermore, the relatively small gap between training and validation performance indicated that the model exhibited good generalization capability and did not suffer from severe overfitting. These findings suggest that CNN optimized with Adam is an effective solution for mushroom image classification and can support intelligent identification systems in food safety, agriculture, and biological image analysis.

Despite the promising results, this study has several limitations, including dependency on dataset quality and the potential influence of image variations such as lighting conditions and visual similarity among mushroom species. Therefore, future research may explore larger and more diverse datasets, deeper CNN architectures, transfer learning approaches, and hybrid optimization strategies to further enhance classification performance and practical applicability.

In conclusion, the integration of CNN and Adam Optimizer provides an efficient and reliable framework for mushroom classification, contributing to the advancement of deep learning applications in biological object recognition and intelligent decision-support systems.

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