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A Convolutional Neural Network Model for Mushroom Toxicity Recognition

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Abstract

Mushroom poisoning remains a public health concern, often caused by misidentifying toxic species that visually resemble edible ones. This study investigates the feasibility of using a Convolutional Neural Network (CNN) to classify five mushroom species, *Amanita caesarea*, *Amanita phalloides*, *Cantharellus cibarius*, *Omphalotus olearius*, and *Volvariella volvacea* into toxic and non-toxic categories based on image data. A dataset of 137 images was collected and preprocessed through resizing, normalization, and data augmentation. A modified AlexNet-based CNN was trained and evaluated using accuracy, precision, recall, and F1-score. The best-performing model achieved a validation accuracy of 0.40, indicating limited discriminative capability. These findings highlight that the dataset size is insufficient for training a CNN from scratch and that the model cannot reliably distinguish species with subtle morphological differences. The study concludes that larger datasets, improved image quality, and transfer learning approaches are essential for achieving practical and deployable mushroom classification performance.

1. Introduction

Mushrooms are one of the most nutritious food sources. They have been known as a food ingredient for over 3,000 years. Historically, mushrooms were served as exclusive dishes for Egyptian royalty, while common people were prohibited from consuming them due to their limited availability [1, 2]. Beyond their use as ordinary food ingredients, mushrooms were also consumed as herbal medicine by Chinese emperors and nobles during the Shu Dynasty, approximately 2,400 years ago. The mushrooms used at that time included Ling-zhi (*Ganoderma lucidum*). In addition, Wood Ear mushrooms (*Auricularia auricula*) were also utilized as herbal remedies [1].

Due to their beneficial properties, public demand for mushrooms increased over time. Initially, people collected mushrooms from their surroundings, forests, gardens, around trees, and grassy areas. However, wild mushrooms are not always readily available. Mushrooms require specific environmental conditions to grow, including adequate water and carbon sources [3, 4]. Consequently, mushrooms do not grow in all seasons, and they typically proliferate during rainy seasons when moisture levels are sufficient. Other environmental factors, such as air pollution, radiation levels, and soil chemical composition, also influence mushroom quality and nutritional content [5, 6].

It is estimated that there are approximately 2.2 to 3.8 million mushroom species worldwide, yet only about 120,000 species had been identified as of 2017 [7]. The vast diversity of mushroom species, combined with the lack of an accessible public information system on mushroom safety, poses a significant risk to individuals

who forage for wild mushrooms, particularly those in rural communities. These communities often rely on wild mushrooms for consumption during rainy seasons. The greatest concern arises from the possibility of misidentifying edible and non-edible species. Furthermore, the general lack of awareness and limited access to reliable information among rural populations increases the probability of misidentification.

Mushrooms are generally categorized into two groups based on edibility: edible and non-edible [8–10]. Edible mushrooms are those that have undergone chemical analysis by experts and have been declared safe for consumption. In contrast, non-edible mushrooms are those that contain toxic substances harmful to the human body.

Among the numerous mushroom species, distinguishing toxic from non-toxic varieties based solely on visual observation is difficult. Some toxic species closely resemble edible ones. For example, *Omphalotus olearius* (toxic) closely resembles *Cantharellus cibarius* (non-toxic), and the button stage of *Amanita phalloides* resembles the Paddy Straw mushroom (*Volvariella volvacea*) [11]. The consequences of incorrectly identifying and consuming toxic mushrooms can be severe, including life-threatening poisoning. Cases of mushroom poisoning have been reported in several regions in Indonesia and abroad.

One such case occurred in Banjarnegara, Central Java, where at least four individuals were hospitalized after consuming wild mushrooms. The victims experienced dizziness, diarrhea, and nausea. One victim stated that the consumed mushrooms resembled those they had eaten previously without adverse effects [12]. Another case, a family in Bangka Regency, Bangka Belitung Province, required intensive hospital care after consuming wild mushrooms. The victims suffered from nausea, diarrhea, blurred vision, dizziness, and severe dehydration. One victim claimed they had searched online for information regarding the mushrooms and found that the species was considered edible if properly processed [13]. A further case occurred in Iran, where wild mushroom poisoning affected approximately 800 people, 11 of whom died. Hundreds of Iranian citizens were hospitalized after consuming wild mushrooms that grew in mountainous areas following the spring season. These mushrooms were widely sold along roadsides, though some individuals harvested them independently [14].

Based on these cases, it is evident that individuals should refrain from picking and consuming wild mushrooms without expert consultation. Such caution is necessary to prevent similar incidents or at least reduce their likelihood. As an effort to mitigate the risk of mushroom poisoning, this study proposes developing a classification model capable of distinguishing mushrooms confirmed to be edible from those confirmed to be toxic. The model accepts an image of a mushroom as input and produces its species name along with a toxicity label as output.

Mushroom images can be captured using imaging devices such as smartphones or digital cameras. Modern imaging technologies have significantly advanced compared to earlier generations. Traditional cameras evolved into digital cameras and eventually into high-quality smartphone cameras. The camera quality of today's smartphones often rivals that of dedicated digital cameras such as Digital Single-Lens Reflexes (DSLRs), at least from the perspective of the average user. Mushroom images for this study can therefore be captured using a smartphone, provided the object is clearly visible. Smartphones are recommended due to their affordability, practicality, and accessibility, although other imaging devices are also acceptable. Moreover, modern smartphone cameras generally produce high-quality images. In addition to their affordability, smartphone usage in Indonesia continues to grow every year. According to a media report summarizing these survey results, smartphone ownership among young adults aged 18–34 rose from 39% to 66% between 2015 and 2018, while ownership among those older than 50 increased from 2% to 13% [15].

The captured images are then divided into training and testing datasets to develop and evaluate the classification model. The model in this study is built using the Convolutional Neural Network (CNN) method. CNNs are an advancement of earlier research in Artificial Neural Networks (ANN), particularly in the field of Computer Vision. CNNs are widely used to develop models capable of distinguishing between two or more categories of image data. In general, CNN architecture combines convolution processes for feature extraction with ANN structures for classification. ANNs consist of interconnected layers of neurons, including an input layer, one or more hidden layers, and an output layer. The deeper the network, that is, the more layers it contains, the more complex the model becomes.

Several cases have demonstrated the effectiveness of CNNs in achieving high classification accuracy. For example, Rangel et al. [16] classified handwritten digits using the MNIST database, achieving an error rate of only 0.23%, a significant improvement compared to earlier methods such as the Baseline Linear Classifier, which produced an error rate of 8.4%. Another widely cited CNN study is the work of Russakovsky et al. [17], who classified

1.2 million high-resolution images into 1,000 categories in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). Their model achieved a top-5 error rate of 15.3%, outperforming the previous best model with a top-5 error rate of 26.2%, developed using SIFT and FV. Rahmadhani and Marpaung [18] conducted a study on classifying edible mushrooms, *Volvariella volvacea*, *Auricularia auricula*, and *Pleurotus ostreatus* into three groups. The CNN model achieved 89% accuracy on the training set and 82% on the test set. The CNN architecture consisted of three convolutional layers, three MaxPooling layers and two dropout layers, to reduce overfitting in the model.

While previous studies have achieved high accuracy using CNNs for mushroom classification, these works rely on large, well-curated datasets. In contrast, there is limited evidence regarding the feasibility of CNN models under extreme data scarcity. This gap is important because in many real-world scenarios, collecting large datasets of mushroom images is challenging, particularly for rare or region-specific species. Therefore, this study aims to explore the baseline performance of a simple CNN model using a highly limited dataset, providing methodological insight into the constraints and requirements of deep learning for mushroom identification.

Across CNN-based studies, one notable aspect is the variation in model architectures. Achieving high accuracy typically requires extensive experiments and parameter tuning, such as adjusting the number of layers, the number of neurons per layer, activation functions, learning rate, and other hyperparameters. This study aims to develop a highly accurate CNN model to distinguish between the mushroom species used as case studies. The mushroom species used in this research include *Amanita phalloides* (toxic), *Amanita caesarea* (non-toxic), *Volvariella volvacea* (non-toxic), *Cantharellus cibarius* (non-toxic), and *Omphalotus olearius* (toxic). These species were selected due to their physical and color similarities, which often make them difficult for laypeople to differentiate. The expected outcome of this research is to assist the public in correctly identifying mushrooms they intend to collect, as misidentifying a toxic mushroom as edible may lead to fatal consequences. This applies specifically to the mushroom species included as case studies in this research.

The primary objective of this study is to develop and evaluate a CNN model capable of classifying toxic and non-toxic mushroom species using image-based features. Specifically, this research aims to address the following questions: (1) whether a CNN model can accurately distinguish visually similar mushroom species with different toxicity levels, and (2) which visual characteristics such as color, texture, and shape, most strongly influence the model's classification performance. Based on these questions, we hypothesize that a CNN trained on sufficiently diverse image data will demonstrate measurable capability in separating toxic species, such as *Amanita phalloides* and *Omphalotus olearius*, from non-toxic species despite their morphological similarities. The intended contribution of this study is to provide an initial benchmark and analytical insight into the feasibility, limitations, and practical challenges of using CNN-based image classification for mushroom identification, particularly as a foundation for developing future intelligent tools that may support public safety and foraging awareness.

2. Materials and Methods

2.1. Dataset Description

The dataset used in this study consists of mushroom images representing five species, comprising both toxic and non-toxic categories. A total of 27 images of *Amanita phalloides* and 27 images of *Amanita caesarea* were included. In addition, 27 images of *Cantharellus cibarius*, 29 images of *Volvariella volvacea*, and 27 images of *Omphalotus olearius* were collected. These images were used as the primary dataset for training and evaluating the classification model, with each species contributing a relatively balanced number of samples to support model stability and reduce potential class imbalance during the learning process.

The present study was initiated by identifying the urgent problem surrounding public difficulty in distinguishing between toxic and non-toxic mushroom species based solely on visual features. Several toxic mushroom species bear a strong resemblance to edible ones, leading to frequent misidentification, which may result in mild poisoning, severe toxic reactions, or even fatal outcomes. To address this issue, this research proposes an image-based classification approach using a Convolutional Neural Network (CNN) to assist in the early identification of mushroom species before consumption.

Formulating the problem required determining the appropriate hyperparameters needed to develop an accurate CNN model. Because the performance of a CNN is highly dependent on hyperparameter configuration, this study examined several influential parameters, including input image size, the number of hidden layers, the number of neurons in each layer, activation functions, number of epochs, convolution kernel size, dropout rate, optimizer type, and learning rate. These hyperparameters were adjusted empirically to determine a configuration capable of achieving the highest classification accuracy while maintaining model stability.

The research made use of computational tools and materials described in Section 3.2. The dataset used in this study consisted of images representing five mushroom species, including two toxic and three non-toxic categories. A total of 137 images were compiled, with approximately 20 images per species allocated for training and 7 images for testing. All images were sourced from Google Images and selected manually to ensure that the visual appearance of each sample corresponded appropriately to the actual morphological characteristics of the species it represented.

2.2. Data Preprocessing and Augmentation

Before training, all images underwent a standardized preprocessing pipeline. First, each image was resized to a uniform dimension to ensure compatibility with the Convolutional Neural Network (CNN) input layer. Pixel values were then normalized to the 0–1 range to improve numerical stability during training.

Data augmentation techniques were applied to enhance the generalization capability of the model, especially given the relatively small dataset size. Augmentation included transformations such as random flips, rotations, and slight zoom adjustments. This step was essential to minimize overfitting and increase the model's robustness to variations in the visual appearance of mushrooms under different conditions.

2.3. Model Architecture

The model developed in this study was based on a modified version of the AlexNet architecture proposed by Krizhevsky et al. [19]. Adjustments were made to the number of layers, neuron configurations, and other architectural components to tailor the model to the characteristics of the mushroom dataset. These modifications were intended to balance model complexity with the need to achieve satisfactory performance despite limited training data.

Hyperparameters considered in model construction included input image size, the number of hidden layers, the number of neurons in each layer, convolution kernel size, activation functions, dropout rate, optimizer type, learning rate, and the number of training epochs. These hyperparameters were adjusted empirically to identify a configuration capable of maximizing accuracy while ensuring model stability.

2.4. Training Procedure

Model training was conducted using 100 images, while the remaining 37 images were reserved for validation. Training was performed for 50 to 150 epochs, depending on the experimental setup. At the start of each epoch, the dataset was shuffled to prevent the model from learning sequential patterns unrelated to the morphological characteristics of the mushrooms. During training, model weights were optimized through backpropagation while validation accuracy was monitored to reduce the risk of overfitting.

Once training was completed, the model was tested using five unseen images, with one image representing each mushroom species. This testing procedure aimed to evaluate the robustness of the model in classifying new samples that were entirely absent from both the training and validation sets. Performance during this stage provided an indication of the model's practical applicability.

2.5. Evaluation Metrics and Validation Strategy

The accuracy of the classification results was calculated by comparing the number of correctly classified test images with the total number of samples evaluated. The model that produced the highest accuracy across multiple training trials was identified as the optimal model. Higher accuracy was interpreted as a sign of improved reliability in identifying mushroom species.

The best-performing model underwent further analysis using a confusion matrix generated from both training and testing results. Based on this matrix, precision, recall, and F1-score were computed to provide additional insights into the model's predictive performance for each mushroom class. These metrics enabled a more comprehensive assessment of model behavior beyond accuracy alone, ensuring a rigorous evaluation of classification performance.

3. Results and Discussion

3.1. Model Configuration

The architecture employed in this study is summarized in Table 1. This configuration closely resembles the original AlexNet architecture; however, several modifications were made to the hyperparameter values and component specifications to better accommodate the characteristics of the mushroom image dataset. The network consists of five convolutional layers, three fully connected layers, and an output layer with five neurons corresponding to the five mushroom classes. Batch normalization and pooling operations were integrated into several convolutional blocks to stabilize learning and reduce spatial dimensionality.

The hyperparameters used for constructing the model are presented in Table 2. The input images were resized to 256 × 256 pixels, while training was conducted using a learning rate of 0.0001, a weight decay of 0.1, and 50

Table 1. Architectural configuration of the modified AlexNet-based CNN model

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	256×256×3	-	-	-
	Convolution	96	62×62×96	11×11	4	ReLU
1	BatchNorm	96	-	-	-	-
	Max. pooling	96	30×30×96	3×3	2	-
	Convolution	256	30×30×256	5×5	1	ReLU
2	BatchNorm	256	-	-	-	-
	Max. pooling	256	14×14×256	3×3	2	-
3	Convolution	384	14×14×384	3×3	1	ReLU
4	Convolution	384	14×14×384	3×3	1	ReLU
	Max. pooling	256	14×14×256	3×3	1	ReLU
5	Convolution	256	6×6×256	3×3	2	-
	BatchNorm	-	-	-	-	-
6	Avg. Pool	256	1×1×256	6×6	1	-
7	F.C.	-	4096	-	-	ReLU
8	F.C.	-	4096	-	-	ReLU
Output	F.C.	-	5	-	-	Softmax

Table 2. Hyperparameter settings used for training the mushroom image classification model

Hyperparameter	Values
Images Size	256×256
Learning rate	0.0001
Weight decay	0.1
Epoch	50
Optimizer	Adam
Batch size	32
Seed	42
Weight initialization	Kaiming Normal

epochs. The Adam optimizer was selected due to its robustness in handling sparse gradients and adaptive learning rates. The batch size was set to 32, and all model weights were initialized using the Kaiming Normal method. A fixed random seed (42) was applied to ensure that model comparisons across experiments could be performed under consistent conditions.

Because the available training data were limited, data augmentation techniques were applied to enrich sample diversity and mitigate overfitting. The augmentation pipeline included rotation, translation, shear transformation, noise injection, horizontal and vertical flipping, center cropping, and blurring. These transformations were essential in increasing the variation of training samples, thereby allowing the model to learn more generalizable feature representations.

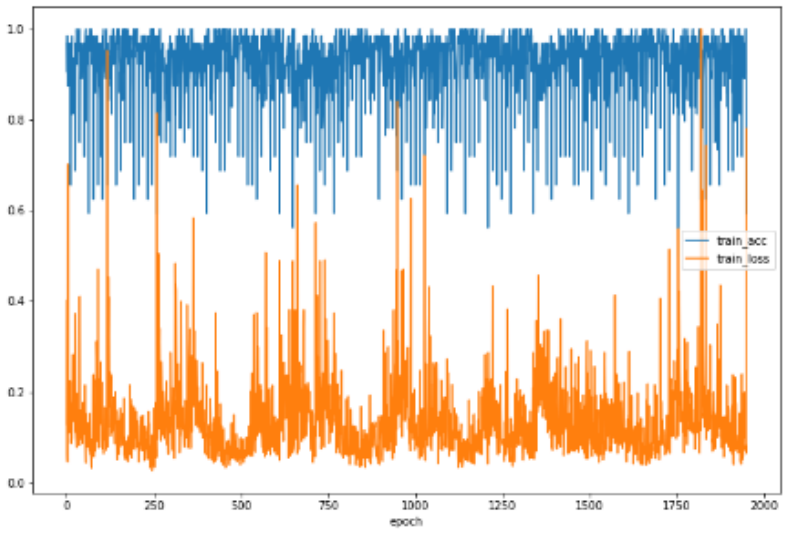
3.2. Training Behavior and Accuracy Fluctuations

The accuracy of the validation data across training iterations exhibited a fluctuating, oscillatory pattern rather than a steadily increasing trend, as shown in Figure 1. One of the primary causes of this behavior is the substantial variation introduced through data augmentation. After each update of the model's weights, samples that were previously classified correctly may be misclassified in subsequent iterations due to the augmented nature of the dataset. This effect recurs across validation samples and contributes to the instability of accuracy values.

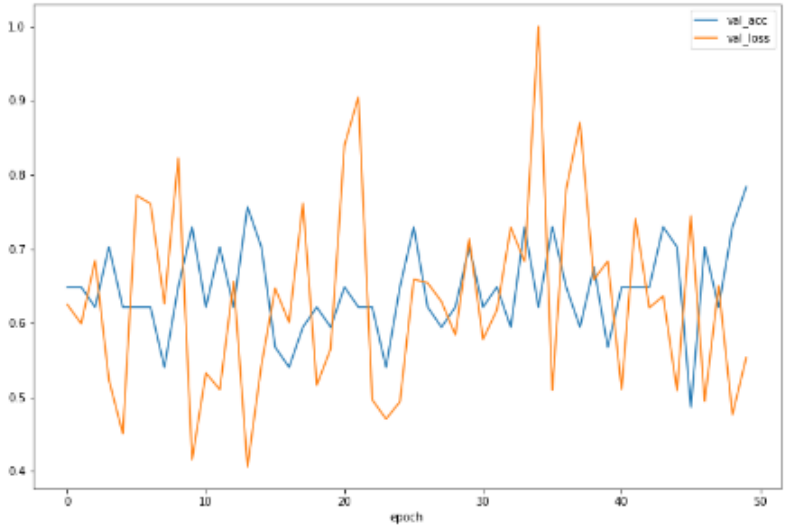
Another contributing factor is the model's architectural complexity. The relatively large number of convolutional and fully connected layers, combined with the high number of neurons in each layer, increases model sensitivity to small weight updates. Consequently, even minor adjustments based on error gradients from a subset of training samples may significantly influence validation accuracy in the following iteration. It is also important to note that both validation and training loss values shown in the graphs were normalized to a range of 0–1.

3.3. Hyperparameter Experiments

To obtain the optimal configuration reported in Table 1, multiple experiments were conducted using various combinations of learning rate and weight decay values. The learning rates evaluated included 0.1, 0.01, 0.001, 0.0001, 0.00001, and 0.000001, while the weight decay values tested were 0.1, 0.01, 0.001, 0.0001, and 0.00001. In each experiment, model weights were initialized using the Kaiming Normal method with a fixed seed value of 42. This approach was intended to simplify the comparison among models by ensuring that differences in



(a)



(b)

Figure 1. Training and validation performance of the modified AlexNet model after the third training run. (a) training accuracy and loss curves. (b) validation accuracy and loss curves.

performance were attributable to hyperparameter variations rather than random initialization effects.

Weight initialization plays a crucial role in determining the convergence behavior of a CNN model. Improper initialization may lead to slow convergence or even divergence during training. Despite the use of a fixed seed and identical initialization strategy, variations still occurred among training runs with the same configuration. This is primarily due to differences in the composition of batches during each epoch, which affect the average error used for weight updates. To assess the consistency and stability of each model, repeated training sessions were performed using the same trained weights from previous experiments. In this study, each model was trained for 50 epochs and retrained at least three times to examine the range of validation accuracy values.

3.4. Effect of Image Resolution

The spatial resolution of the training images also influenced the model's performance. Additional experiments were conducted using image resolutions of 128 × 128 and 80 × 80 pixels. The validation accuracy curves associated with these resolutions displayed substantial fluctuations across iterations, as illustrated in Figure 2. In contrast, the 256 × 256 resolution used in the final model produced comparatively more stable accuracy values and superior performance. These results indicate that higher-resolution images enable the network to extract more informative features, which is particularly important for distinguishing subtle visual differences among mushroom species.

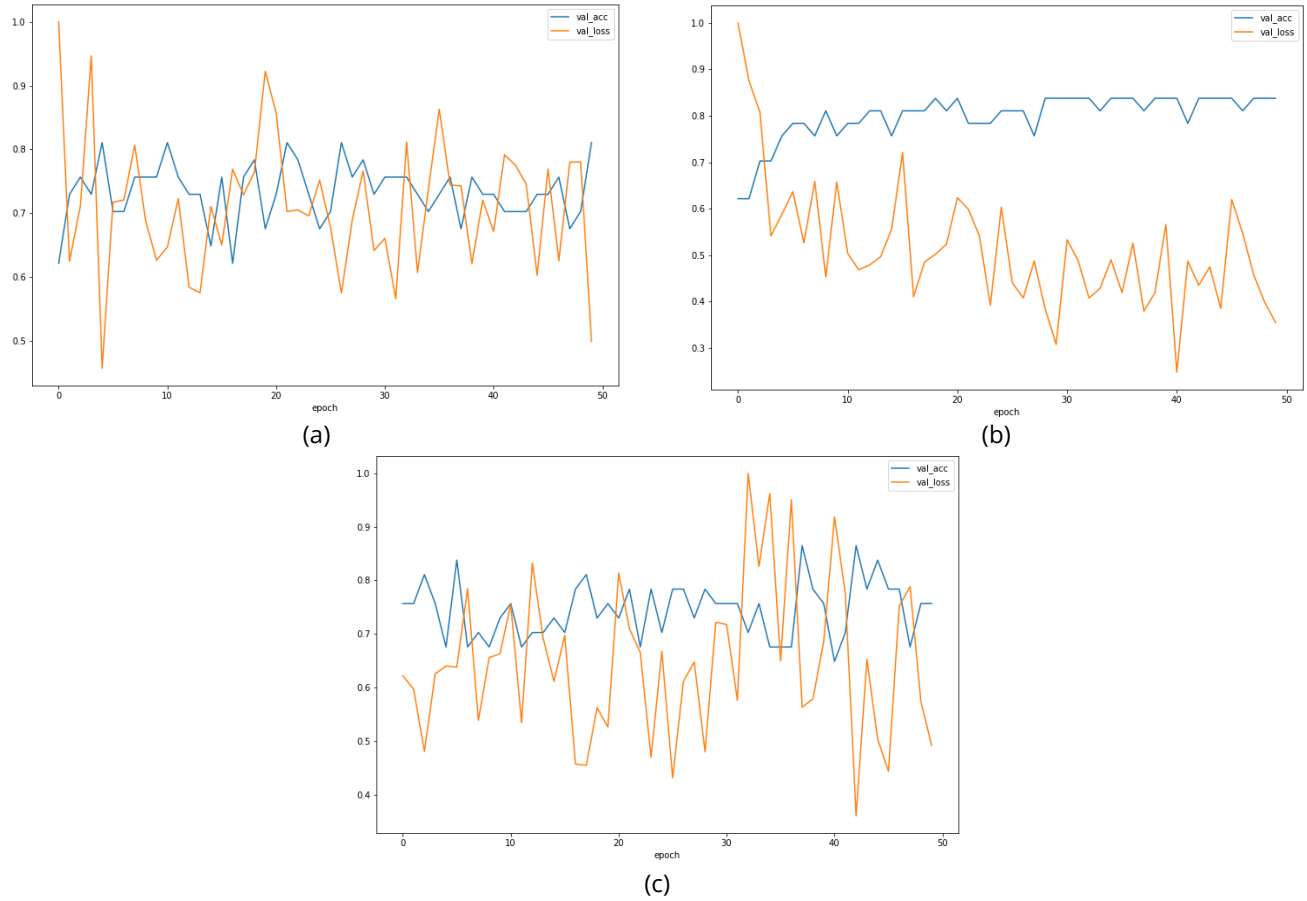


Figure 2. Validation accuracy of the modified AlexNet model after the third training session. (a) accuracy curve using 80×80 training images. (b) accuracy curve using 256×256 training images. (c) accuracy curve using 128×128 training images.

Table 3. Architectural configuration of the modified AlexNet-based CNN model.

		Prediction				
		O. olearius	*A. caesarea*	*C. cibarius*	*V. volvacea*	*A. phalloides*
Ground truth	*O. olearius*	1	6	0	0	0
	A. caesarea	0	5	0	0	2
	C. cibarius	0	3	2	0	2
	V. volvacea	0	0	0	0	9
	A. phalloides	0	0	0	0	7

3.5. Model Performance

After completing the training process using the training dataset and subsequent evaluation using the validation dataset, the model was re-evaluated with the same validation data to determine its post-training classification accuracy. The resulting validation accuracy was 0.40, indicating limited performance in distinguishing between mushroom species. To better understand the sources of misclassification and the factors contributing to the low accuracy, a confusion matrix was generated, as shown in Table 3.

Analysis of the confusion matrix revealed substantial inconsistencies in the model's predictions across classes. The precision values for *O. olearius*, *A. caesarea*, *C. cibarius*, *V. volvacea*, and *A. phalloides* were 1.00, 0.35, 1.00, 0.00, and 0.35, respectively. These results suggest that the model exhibited weak overall classification performance, with a considerable number of samples being incorrectly predicted. For instance, none of the *V. volvacea* images were correctly classified. Although *O. olearius* achieved a precision score of 1.00, the recall was only 0.16, meaning that only one of the six actual samples was correctly identified while the others were misclassified as different species. The model performed relatively better for *A. caesarea*, correctly predicting five out of seven samples, and for *A. phalloides*, all samples were classified correctly. However, the model failed to learn discriminative features that separate *V. volvacea* from *A. phalloides*, likely due to similarities in pixel intensities and visual characteristics, particularly their predominantly white coloration. For *C. cibarius*, only two images were correctly identified, while three and two samples were misclassified as *A. caesarea* and *A.*

Table 4. Evaluation of precision, recall, and F1-score for each mushroom species.

Species	Precision	Recall	F1-Score
O. olearius	1.0	0.16	0.27
A. Caesarea	0.35	0.71	0.46
C. cibarius	1.0	0.28	0.43
V. volvacea	0.0	0.0	NaN**
A. phalloides	0.35	1.0	0.51

Figure 3. Selected mushroom species for the experiment: *A. caesarea*, *A. phalloides*, *C. cibarius*, *V. volvacea*, and *O. olearius*. (Source: https://images.google.com).

Table 5. A confusion matrix for a new dataset.

		Prediction				
		O. olearius	*A. caesarea*	*C. cibarius*	*V. volvacea*	*A. phalloides*
Ground truth	*O. olearius*	1	6	0	0	0
	A. caesarea	0	5	0	0	2
	C. cibarius	0	3	2	0	2
	V. volvacea	0	0	0	0	9
	A. phalloides	0	0	0	0	7

phalloides, respectively. A detailed summary of these performance metrics can be found in Table 4.

The precision, recall, and F1-scores for each species further demonstrate the model's limitations. *V. volvacea* exhibited a precision and recall of 0.0, resulting in an undefined F1-score due to division by zero. Meanwhile, *A. phalloides* achieved a recall of 1.00 but suffered from relatively low precision, indicating that the model frequently misclassified other species as *A. phalloides*. These inconsistencies suggest that the model may be biased toward certain visual features that are not sufficiently discriminative across all species.

To further assess the model's generalization ability, an additional experiment was conducted using five new mushroom images not included in either the training or validation datasets (As presented in Figure 3). Each species was represented by one image. The prediction results for these new samples are presented in Table 5. The outcomes indicate that color served as one of the primary separation features learned by the model, alongside morphological characteristics. Mushrooms with yellowish tones, such as *O. olearius* and *C. cibarius*, were predominantly misclassified as *A. caesarea*. In contrast, mushrooms with pale or whitish coloration, such as *V. volvacea*, were predicted as *A. phalloides*. These findings suggest that the model's decision boundaries rely heavily on dominant color information, which may be insufficient for accurately distinguishing species with overlapping visual characteristics.

The findings of this study must be interpreted with caution due to the fundamental limitation posed by the very small dataset. With only 137 images in total, the model may not have been able to learn meaningful discriminative features, particularly for species with subtle morphological differences. The relatively low validation accuracy observed in several experimental configurations likely reflects the effects of random variance rather than true model capability. Without transfer learning or a substantially larger dataset, training a CNN from scratch is prone to overfitting and unreliable performance estimation. Therefore, the reported results should be considered preliminary and should not be viewed as indicative of actual classification reliability.

4. Conclusions

This study evaluated the capability of a CNN model to classify five mushroom species, comprising two poisonous (*A. phalloides*, *O. olearius*) and three non-poisonous species (*A. caesarea*, *C. cibarius*, *V. volvacea*). The results show that the developed model is not yet reliable for practical use as a tool for distinguishing poisonous from non-poisonous mushrooms. While the model demonstrated some ability to identify color- and shape-based features, frequent misclassifications occurred, particularly among species with similar visual attributes. The model also showed a tendency to overpredict the classes *A. phalloides* and *A. caesarea*, indicating class bias and limited feature differentiation.

Moreover, the model exhibited high sensitivity to weight initialization, where small variations in weight values resulted in notable changes in prediction outcomes. This instability, coupled with the model's inability to recognize species-specific morphological characteristics, limited its classification performance.

Nevertheless, this study has several limitations. The dataset size was relatively small, which restricted the model's ability to generalize and contributed to class imbalance. The images also lacked uniformity in lighting, background, and orientation, potentially influencing feature extraction. Additionally, only one CNN architecture (AlexNet-based modification) was tested, limiting the scope of comparison across more advanced or specialized architectures.

Future research should prioritize expanding the dataset through field image collection, web-based data aggregation, or the use of publicly available mushroom image repositories to provide sufficient variability for model training. Additionally, applying transfer learning using pretrained architectures such as VGG16, ResNet, or MobileNet is strongly recommended to overcome data scarcity and improve model generalizability. These strategies will enable the development of a more robust and reliable image-based mushroom classification system.

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