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Deep Learning Based Approach for Classification of Mushrooms

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Keywords

CNN

Image Processing

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Abstract

Deep learning algorithms have produced amazing results in recent years when used to identify items in digital photographs. A deep learning technique is suggested in this work to classify mushrooms in their natural habitat. The study's objective is to identify the most effective method for categorizing mushroom images produced by well-known CNN models. This study will be helpful for the field of pharmacology, mushroom hunters who gather mushrooms in the wild, and it will help to lower the number of people who are at risk of becoming ill from poisonous mushrooms. Images are taken from data labelled by INaturalist specialist. The photographs show mushrooms in their natural environment and feature a variety of backgrounds. The "Mobilenetv2_GAP_flatten_fc" model, which was the study's top performer, had a training data set accuracy of 99.99%. It was 97.20% accurate in the categorization that was done using the validation data. Using the test data set, the classification accuracy was 97.89%. This paper presents the results of a performance comparison between the best-performing model and a multitude of state-of-the-art models that have undergone prior training. Mobilenetv2_GAP_flatten_fc model greatly outperformed the trained models, according to the precision, recall, F1 Score. This illustrates how the basic training process of the suggested model can be applied to enhance feature extraction and learning.

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1. INTRODUCTION

Mushroom cultivation is a process by which people grow mushrooms for food, beverage or medicinal purposes. Mushrooms are one of the most alluring and fascinating of nature's many secrets. People who have lived in close proximity to nature for thousands of years have learned that mushrooms are not just a wonderful food but also a window into the complexity and beauty of nature. There are many different types of mushrooms in the globe, but only a small number of them are edible to humans. On the other hand, poisonous mushrooms might result in major health issues if they are not adequately identified and thrive in the same habitats. Therefore, it is crucially important to identify and categorize mushrooms. For a model to learn about thousands of items from millions of images, it needs to have a large learning capacity (Jarrett et al., 2009). The object recognition problem is so complex that it cannot be adequately described even with a dataset as extensive as ImageNet (Lee et al., 2009). Therefore, the model used in the study must incorporate a substantial amount of prior knowledge to compensate for the unavailability of certain data. Convolutional neural networks (CNNs) are a subset of deep learning models and assumptions they make about the properties of images are powerful and generally correct (Pinto et al., 2009). These assumptions can be exploited to make the network's general-purpose features more specific and optimized in a particular context (Turaga et al., 2010). Hence, CNNs possess significantly fewer connections and parameters when compared to standard feedforward neural networks of similar-sized layers, rendering them more amenable to training (Krizhevsky et al., 2012). This work offers a classification of harmful and healthy mushrooms. In order to comprehend the diversity of the

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natural environment and minimize health hazards, mushroom taxonomy is crucial. In addition, it's crucial to comprehend how to recognize these species, what traits to look for, and why some mushroom species are poisonous to ingest in order to make mushroom gathering and consumption safer in the wild. In this study, the "Mobilenetv2_GAP_flatten_fc" network, a state-of-the-art CNN framework for the classification of mushrooms, was examined. The 'Mobilenetv2_GAP_flatten_fc' model, enriched with multiple architectural layers and a fundamental training strategy, successfully classified dangerous mushrooms. In a comparative study, our approach exhibited slightly superior results when compared to comparable pre-trained CNN models. The findings are viewed as optimistic, leading one to conclude that this research will benefit:

- Pharmacology: The study of drugs and medications.
- Mushroom hunters: Individuals who gather mushrooms, often for various purposes, such as cooking or medicinal use.
- Human health: The overall well-being and medical conditions of people.
- Mushrooms are described as a part of biodiversity, which refers to the variety of life on Earth.
- It is emphasized that precise classification of mushrooms can have a role in recognizing and safeguarding biodiversity. This implies that correctly identifying and categorizing mushrooms can contribute to the understanding and conservation of various species and ecosystems on Earth.

2. LITERATURE REVIEW

Nusrat, Zahid, and the other researchers focused on the detection of distinct mushroom species in their investigation. They classified 8190 photos of mushrooms using deep learning techniques including InceptionV3, VGG16, and Resnet50 (Zahan et al., 2021). They chose an 8:2 split between training and test data. They compared contrast-enhanced and non-contrast-enhanced approaches using InceptionV3 and the Contrast Limited Adaptive Histogram Equalization (CLAHE) method to get the maximum test accuracy. When compared to other algorithms, InceptionV3 has the greatest success rate with 88.40% accuracy. In their research, Mark and Meo created a system to categorize six mushrooms using Convolutional Neural Network (CNN) deep learning models integrated with Raspberry Pi (Sutayco & Caya, 2022). They trained 600 example mushroom images using the CNN-Inception-V3 architecture that has already been taught. For model training and validation, they used 80% and 20% of the data, respectively. The final model's total accuracy was 92.7%. In Yunnan Province, a location rich in natural mushroom resources in China, Hui, Fuhua et al. trained VGG16, Resnet18, and Googlenet models using data of diverse mushrooms with varied features and combined them with the bagging technique (Zhao et al., 2021). As a result, by adjusting to complex cues in the natural mushroom recognition process, accuracy and generalization capacity are enhanced. The model fared better than a single CNN, according to experiments. The integrated model had an accuracy of 93.1% using a 10% validation dataset, whereas the best single bagging integrated model had an accuracy of 90.8%. Wacharaphol et al. addressed the issue of finding the difference between edible and dangerous mushrooms due to their similar appearance in their study (Ketwongsa et al., 2022). They classified the toxic and edible varieties of five commonly encountered mushroom species in Thailand, including Inocybe rimosa, Amanita phalloides, Amanita citrina, Russula delica, and Phaeogyroporus portentosus, using convolutional neural networks (CNN) and region convolutional neural networks (R-CNN). The goal of this study was to lessen the amount of fatalities brought on by the intake of toxic mushrooms. Three pre-trained models—AlexNet, ResNet-50, and GoogLeNet—were compared in the study for test time and accuracy. Their suggested model required less time for testing and training while still being highly accurate. In R-CNN studies for mushroom classification, their suggested model had accuracy scores of 95.50%.

3. MATERIALS AND METHODS

3.1. Dataset

For the investigation, a sizable fungal data set made up of 224x224x3 photos of 4 distinct mushrooms was gathered. Coprinus comatus (ink mushroom), Amanita pantherina (panther mushroom), Fistulina hepatica (beefsteak mushroom), and Craterellus cornucopioides (borer mushroom) are the mushrooms utilized in the dataset. Table 1 lists the many varieties of mushrooms and their quantities.

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Table 1. *Types of Mushrooms in The Dataset*

Mushroom Type	Number of Data
Coprinus comatus (ink mushroom)	1,480
Amanita pantherina (panther mushroom)	1,500
Fistulina hepatica (beefsteak mushroom)	1,500
Craterellus cornucopioides (borer mushroom)	990
Total	5,470

Images of mushrooms were gathered from the iNaturalist website. Nature lovers can submit their observations, images, and documentation of plants, animals, insects, and other living species in the database known as iNaturalist. Since different image capture tools (smartphones, digital cameras, etc.) were used to take the mushroom images, the photos' resolution and format differ. The collected mushroom data set was uploaded to the Figshare platform to be accessible to everyone under the title Mushroom Classification (Demirel & Demirel 2023). The requirement that the images be homogeneous is one of deep learning networks' essential elements. Therefore, before using any deep learning model, the raw images must go through the required preprocessing. In this experiment, A Python script first reduced each image's resolution to 224 224 3 pixels utilizing the Python Imaging module and then utilized for model training. Each image was saved in its own folder on the storage devices in the.jpg format. For standardization, the photos were then read from the storage devices and transformed into numpy arrays using the 'NumPy' package. During model training, reading and processing photos is made efficient via Numpy arrays. These 224 224 224 224 3 numpy arrays served as the input for the suggested model for feature extraction and classification. The Amanita pantherina (Panther mushroom) and Fistulina hepatica (Beefsteak mushroom) classes in this experiment have much more images than the other two classes. To improve the model's performance, increase its capacity for generalization, correct imbalances, and encourage the model to learn from a wider range of samples, data augmentation was carried out. This was done using the Python library 'Augmentor'. The altered photographs were used to create the false visuals, but the labels on the original photos were left intact. The volume and variety of the dataset were to be increased through this image augmentation. Several strategies were used for data augmentation in this study. Randomly chosen training images were rotated by 10 degrees, magnified by 10% of the width, shifted vertically by 10% of the height, and randomly shifted horizontally by 10% of the width. The data pool was thus expanded. Figure 1 shows sample images from the dataset used. Figure 2 shows the distribution rates of the data set.

Figure 1. *Analysis of the Data*

Figure 2. *Data Distribution*

3.2. Classification Approach

Currently, computer vision and pattern recognition are being advanced by deep convolutional neural networks (CNNs). CNNs have the capacity to automatically learn the differentiating characteristics of images/objects from pixel arrangements in images, in contrast to typical machine learning methods where classifiers are trained using manually created image attributes.

In this experiment, the photos were classified with the "Mobilenet-V2_GAP_flatten_fc" model, which is an improvement of the "Mobilenet-V2" CNN model, a well-known example of a modern convolutional neural network. Since MobileNetV2 is small and efficient, it can work well even on computers with limited memory and processing capacity. Using a deep learning method, this model may be applied to tasks including image categorization, object recognition, and image segmentation. A validation error rate of 2.80% and a test error rate of 2.11% were recorded during the evaluation with the "Mobilenet-V2_GAP_flatten_fc" network.

The study utilizes the Mobilenet-V2_GAP_flatten_fc model. MobileNetV2 networks are specifically designed for mobile, IoT, or low-hardware devices, offering substantial enhancements in both parameter count and computational complexity while maintaining high classification performance (Chen et al., 2020). Linear bottleneck and inverted residuals block within the architecture lead to a substantial reduction in the required memory (Zhang et al., 2019). The convolution layer is composed of depth access and point access layers (Sandler et al., 2018). Figure 3 shows the MobileNetV2 architecture (Seidaliyeva et al., 2020).

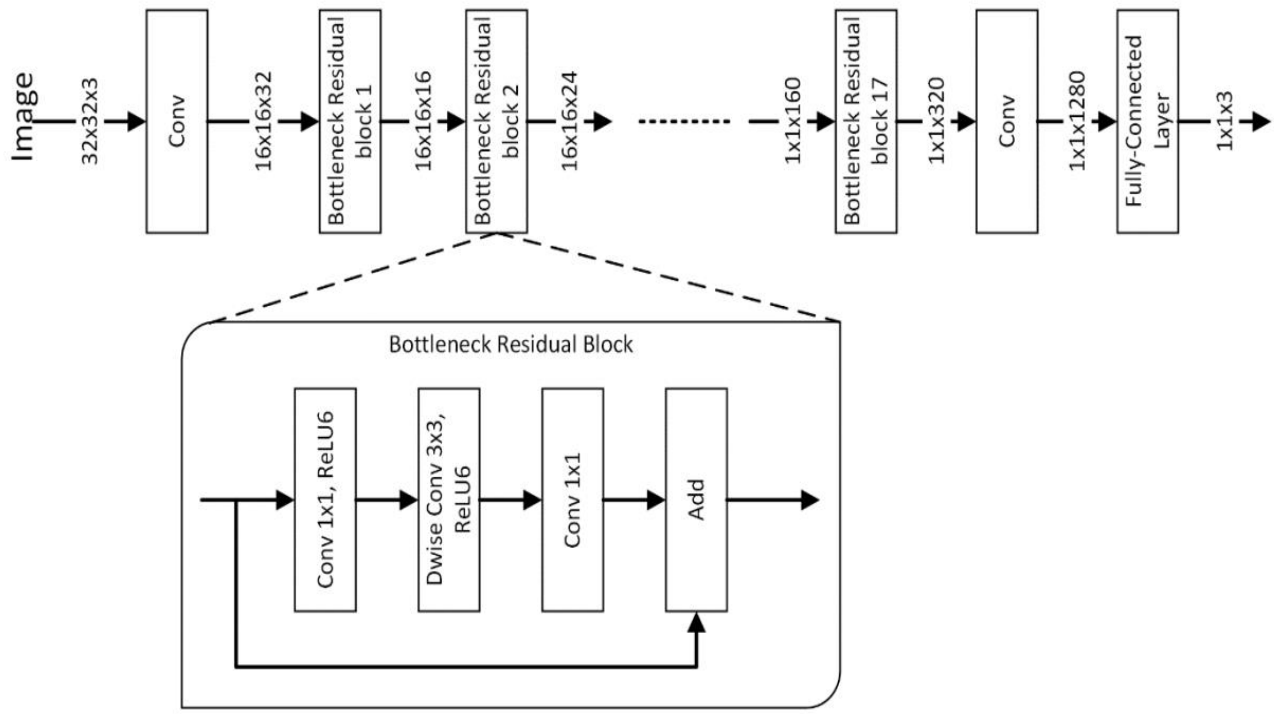

Figure 3. *MobileNetV2 Architecture*

On a field image dataset created from mushroom photographs, the models' performance was assessed and compared. A straightforward training strategy was used, in which the mushroom dataset was used to train all layers of the models. The weights were initialized randomly throughout the training phase rather than being pre-trained for the models. For both the training and validation datasets, Mobilenet-V2_GAP_flatten_fc was trained for 100 iterations. The results part included an ablation study for cycle and chunk selection.

Adam optimization was performed with a learning rate of 0.001 and default hyperparameter values. Hyperparameters utilized man optimization. 1e-3 was used as the learning rate. The training rate used throughout training was 0.000000001. The effectiveness of the suggested strategy in this research was compared to the pre-trained models. Figure 4 illustrates the model and its respective layers employed in the study.

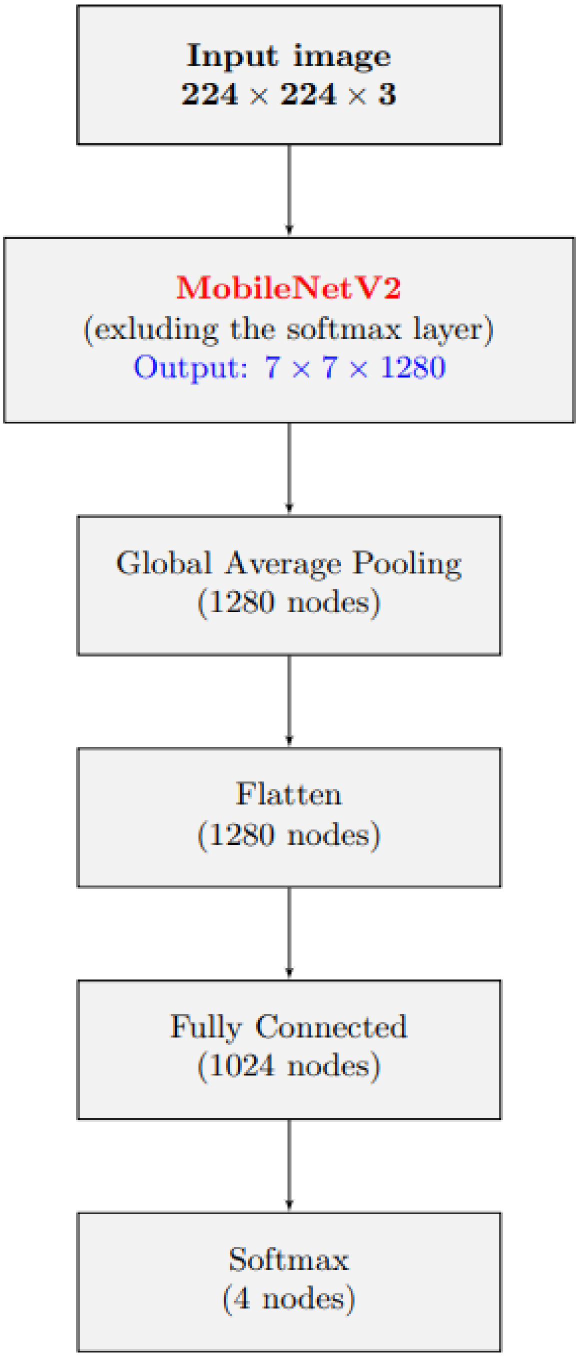

Figure 4. *MobileNetV2_GAP_flatten_fc*

3.3. Application

The Python programming language's Keras high-level TensorFlow API was used to implement each model. Table 2 provides specifics on the hardware and software configuration.

__Table 2.__ Hardware and Software Configuration

Name	Parameters
Operating System	Windows 10 Home Single Language 64 bit
CPU Processor	Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz 1.80 GHz
GPU (Graphics Processing Unit)	Intel(R) UHD Graphics 620
RAM	12,0 GB
Deep Learning Framework	Keras library running on TensorFlow
Deep Learning Environment	Google Colab Notebook
Programming Language	Python

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

4.1. Performance Metrics

The entire dataset was split into three sections: training, validation, and test sets in order to fairly assess performance. Initially, the total dataset was split 80:20, with 80% of the data used for training and validation and 20% kept separate for testing/evaluating the models after training. Then, the remaining 80% of the data was split in half using different configurations for training-validation tasks. Table 3 provides a summary of the various training-validation setups for the dataset. To ensure that each partition had photos from both the original dataset and the enhanced dataset, the original and enhanced data were split into different partitions and then mixed. A Python script handled all data splitting. A separate 20% test dataset was used in each experiment to test the models after training and validation. It should be emphasized that photos from both the original and supplemented datasets were included in the data used to evaluate all models. Performance metrics used in the study:

Recall (Sensitivity) is calculated by the ratio of true positive classes to all the actual positive classes in the input images. Recall is calculated using the mathematical expression shown in Equation 1.

$$\text{Recall} = TP / (TP + FN) \tag{1}$$

Precision is calculated by the ratio of true positive results in the input that were correctly predicted as positive. Precision is calculated using the mathematical expression shown in Equation 2.

$$\text{Precision} = TP / (TP + FP) \tag{2}$$

Accuracy is generally used to decide whether the model is correct or not, but it is not a sufficient criterion on its own to evaluate whether the model is good or bad. Accuracy is calculated using the mathematical expression shown in Equation 3.

$$\text{Accuracy} = (TP+TN) / (TP+TN+FP+FN) \tag{3}$$

F1 Score provides a combined assessment of performance criteria such as sensitivity and accuracy. The F1 Score is calculated using the mathematical expression shown in Equation 4.

$$\text{F1 Score} = 2TP / (2TP+FP+FN) \tag{4}$$

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These equations and concepts are commonly employed in the context of binary classification. In scenarios where classification involves three or more classes, performance evaluation measurements are typically averaged.

The performance of the models for mushroom-wise categorization was then determined by creating complexity matrices. The following variables are provided by the complexity matrix. The MobileNetV2_GAP_flatten_fc model evaluation results are once again shown in Table 3 along with performance metrics.

Table 3. *Performance Evaluation Results for the MobileNetV2_GAP_flatten_fc Model*

Mushroom Type	Precision	Recall	F1 Score
Coprinus comatus (Ink mushroom)	0.95	0.96	0.95
Amanita pantherina (Panther mushroom)	0.97	0.99	0.98
Fistulina hepatica (Beefsteak mushroom)	0.97	0.97	0.97
Craterellus cornucopioides (Borer mushroom)	0.96	0.92	0.94

5. COMPARATIVE ANALYSIS WİTH PREVIOUS STUDIES ON FUNGAL CLASSIFICATION

Here, a comparison of our suggested strategy and others suggested in the literature for mushroom classification is shown in Table 4. This comparison shows that, when compared to earlier studies, our suggested approach is quite successful at classifying mushrooms. Figure 5 illustrates the accuracy matrix for the MobileNetV2_GAP_flatten_fc model, while Figure 6 shows the validation matrix for the same model.

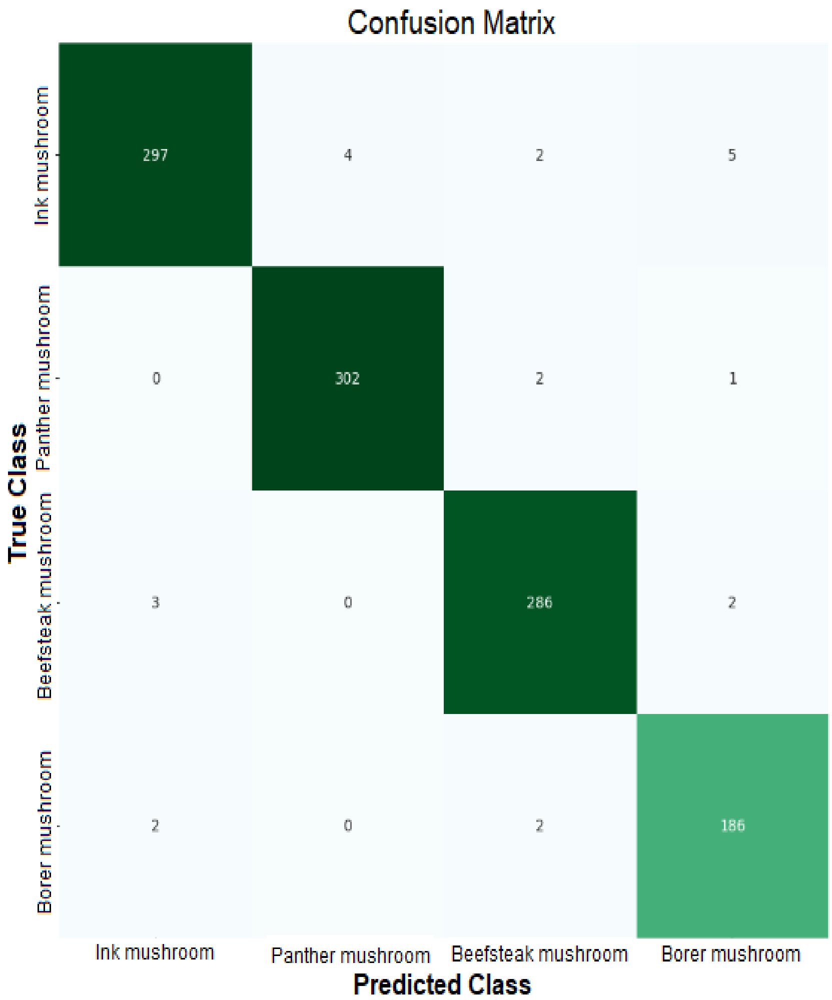

Figure 5. *Accuracy Matrix for MobileNetV2_GAP_flatten_fc Model*

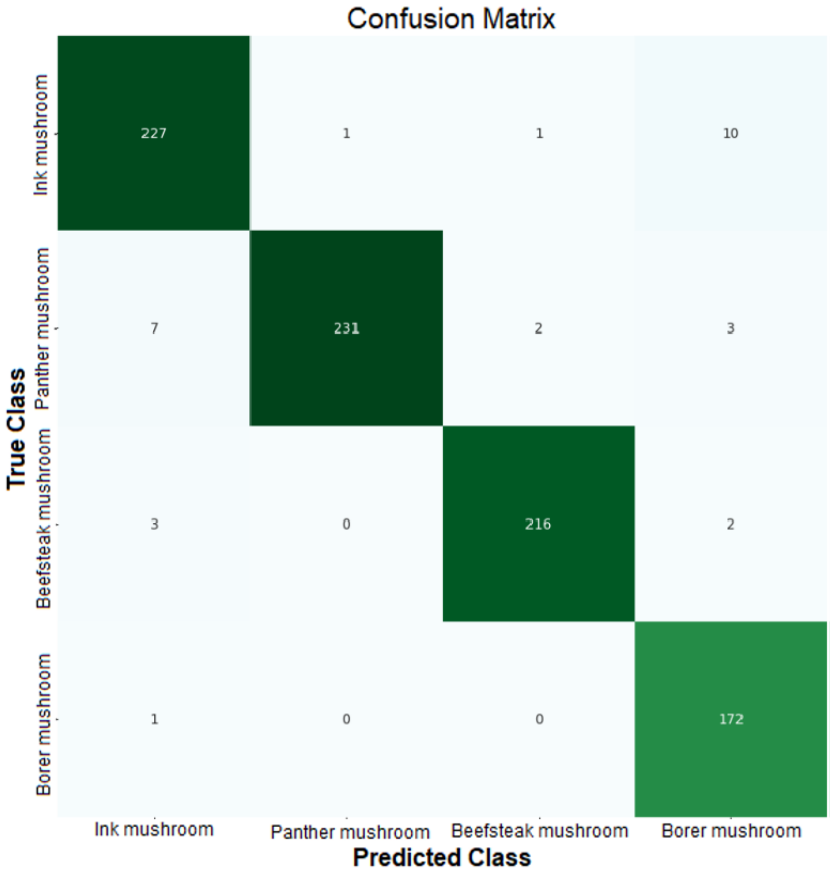

Figure 6. *Validation Matrix for MobileNetV2_GAP_flatten_fc Model*

Table 4. *Comparison of the Proposed Approach with the Approaches Found in the Literature for Mushrooms*

	Number of Images	Model	Number of Classes	Accuracy	Year
Mark and Meo	600	InceptionV3	6	%92,7	2022
Hui et al.	13.587	VGG16, ResNet18 ve GoogleNet	27	%93,1	2021
Wacharaphol et al.	623	AlexNet, ResNet-50 ve GoogLeNet	5	%95,50	2022
Boyuan	9528	Vi-T/L32	11	%95,97	2022
Nusrad, Zahid et al.	8190	InceptionV3, VGG16 ve Resnet50	45	%88,40	2021

6. ABLATION STUDIES

Several experiments were conducted on various batch sizes and epochs in order to determine the best ones to use during the model training phase. As observed in Figures 7 and Figure 8, the test accuracy rises as the training time per epoch falls up to 32 batches. Figure 8 displays the experimental outcomes of the Mobilenet-V2_GAP_flatten_fc model trained with batch sizes of 16, 32, 64, and 128 images. Test accuracy declines after 32 batches. Model training had its best performance with a batch size of 32. Test accuracy measurements for 100 model training epochs are shown in Figure 9. The test accuracy is seen to gradually rise with epoch until it approaches 100. The epoch was chosen for 100 iterations because after 100 epochs, the model begins to overfit the dataset. Figure 9 displays the training and validation success and failure for 100 epochs.

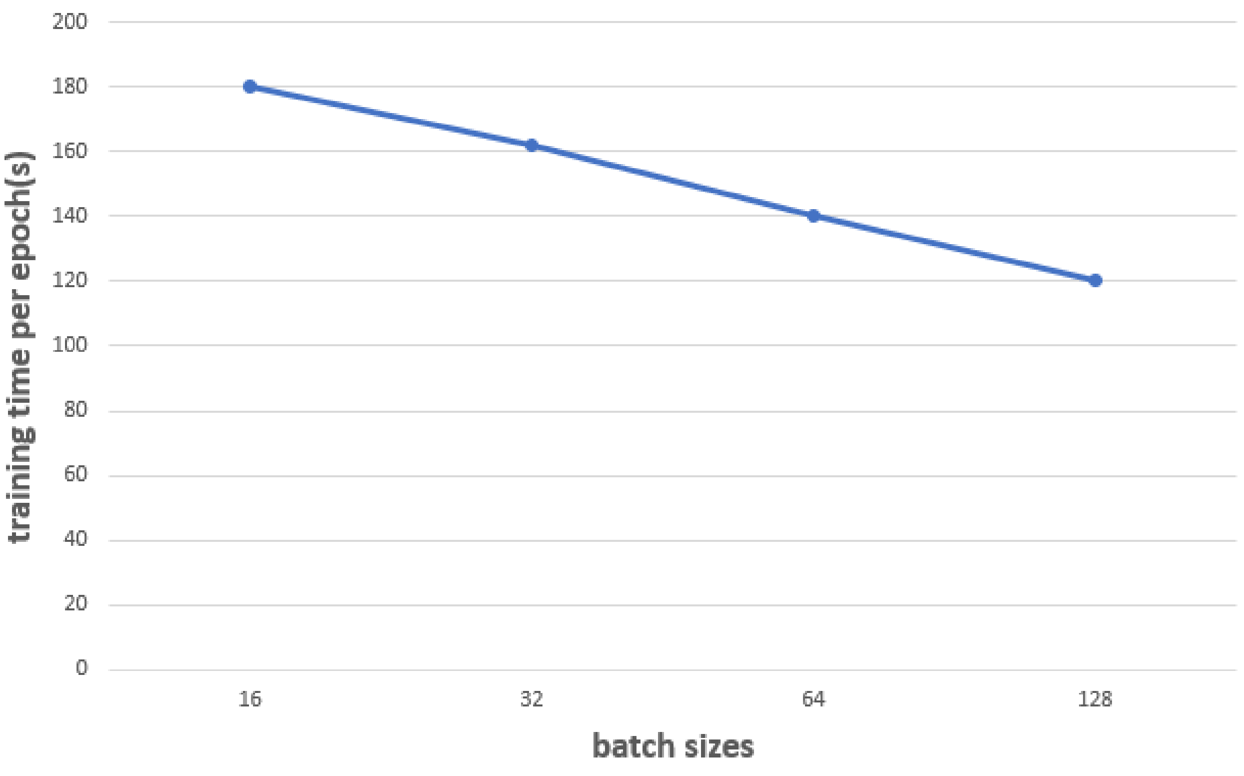

Figure 7. *Effect of Batch Sizes on the Performance of the Model*

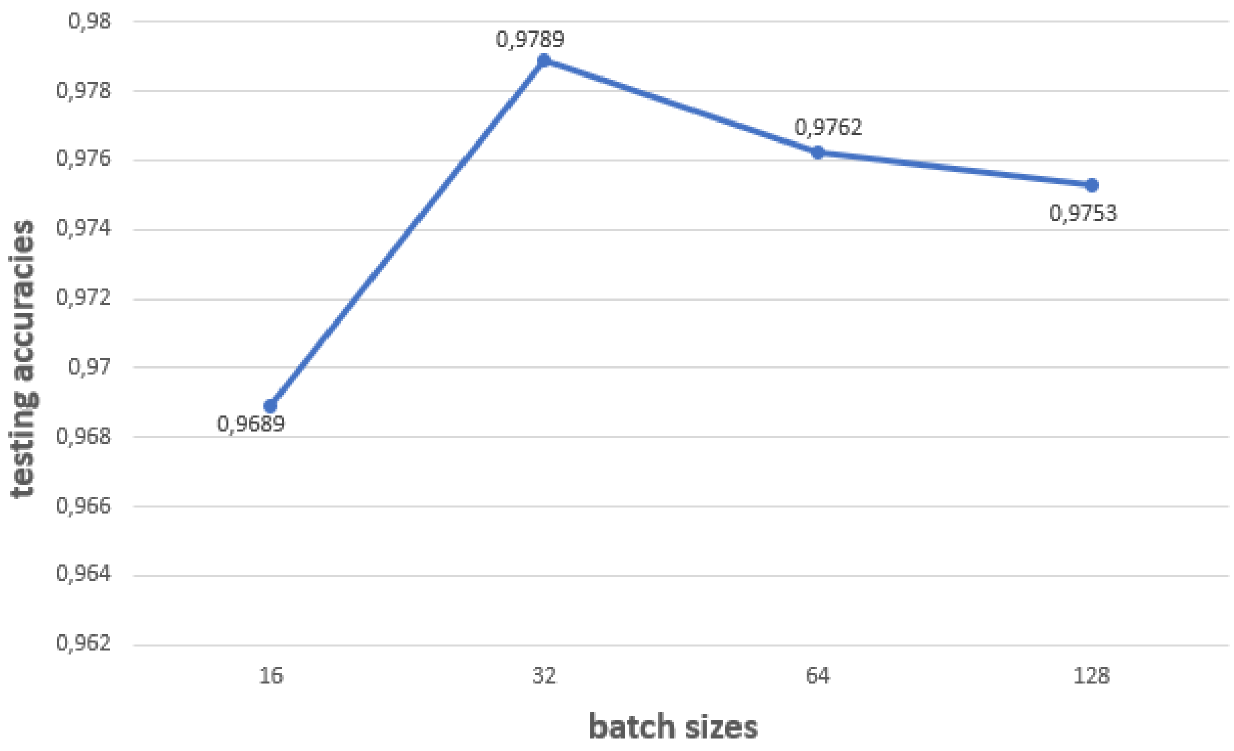

Figure 8. *Batch Size in Relation to Training Time Per Epoch and Batch Size in Relation to Model Accuracy Testing*

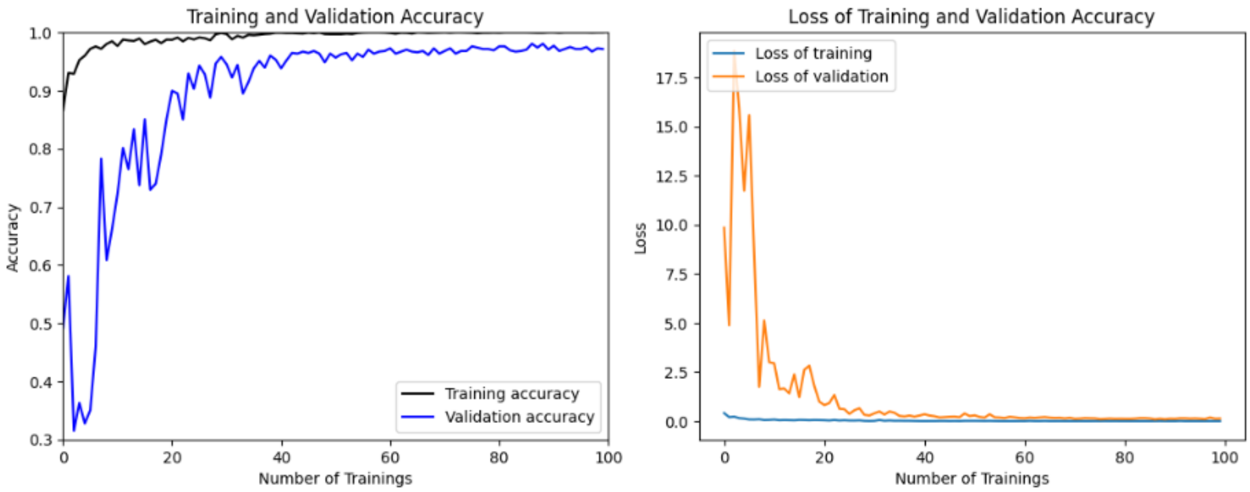

Figure 9. *Accuracy and Loss in the Training Process for the MobileNetV2 Model*

7. DISCUSSION

A thorough comparison analysis of a range of pre-trained modern facilities networks is also carried out to show the success of the suggested technique. Transfer learning was employed by utilizing pre-trained models. The comparative results demonstrate that the MobileNet-V2 model has a lower computational expenditure in terms of its training time and parameter count when compared to the pre-trained models. Nevertheless, the MobileNet-V2 model performed well in precisely categorizing mushrooms based on the attributes discovered from the studied data, in addition to having a low computational cost. It can be argued that deep CNN models can learn both low-level and high-level features from the input images during their basic training, and this training also produces impressive outcomes of the dataset under study's classification.

In the future, the envisioned model will seamlessly integrate with a mobile application, offering an advanced tool for real-time disease identification. This will make it easier for mushroom growers to automatically diagnose disease symptoms without requiring the involvement of field experts or extension workers. Thus, timely management of diseases and prevention of poisoning caused by fungi will be ensured.

8. CONCLUSION

In this article, a method based on deep convolutional neural networks is suggested to automatically recognize digital pictures of mushrooms. The training, validation, and test datasets are created by randomly dividing a collection of 5470 photos of four different types of mushrooms.

In order to provide additional evidence of the effectiveness of the proposed approach, an extensive comparative analysis of several state-of-the-art networks that have already been trained was performed Pre-trained models were employed through a transfer learning approach. Comparative results reveal that, in terms of training time and parameter count, the Mobilenet-V2_GAP_flatten_fc model exhibits a higher computational cost compared to other pre-trained models. The Mobilenet-V2_GAP_flatten_fc model performed a considerably better job of reliably diagnosing the disease symptoms utilizing learned features from the research data, despite its high computing cost. From the input photographs, it was inferred that deep CNN models trained on baseline can also extract both high-level and low-level features. It was observed also pretty good classification results on the dataset that is being studied.

The mushroom dataset's fundamental structural architecture serves as the basis for modeling the cutting-edge "Mobilenet-v2" network. In these architectures, base learning is used, and the mushroom dataset is used to train all of the computational layers. According to experimental findings, Mobilenet-V2_GAP_flatten_fc model was evaluated by looking at recall, precision, accuracy, F1 score performance evaluation criteria. In this evaluation, Macro Average values were examined for the results. As a result of the evaluation, it was seen that the best results for sensitivity, precision and F1 score in the test data set were 97.91%, 97.71%, 97.80%, respectively. In addition to accurately predicting class levels based on unobserved data, the MobileNetV2 model was effective at learning mushroom-related properties. According to this study, deep learning approaches provide highly promising outcomes for mushroom identification.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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