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Analysis and Development of Eight Deep Learning Architectures for the Classification of Mushrooms

Lia Farokhah[1], Suastika Yulia Riska[2]
[1,2]Informatics, Technology and Design, Institut Teknologi dan Bisnis ASIA, Malang, Indonesia
[1]farokhah@asia.ac.id, [2]riska.suastika@asia.ac.id

Abstract

One food item that is easy to find in nature is the mushroom. In terms of form and features, mushrooms are similar. Arranging mushrooms into groups so that poisonous and non-poisonous ones can be told apart is important. Real-time analysis of mushrooms is still not used very often. Previous studies focused primarily on performance and accuracy, ignoring architectural computing and a significant amount of data preprocessing. The used dataset is more laboratory-conditioned. This will impede the process of widespread implementation. The study suggests changes to eight current architectures: Modified DenseNet201, DenseNet121, VGG16, VGG19, ResNet50, InceptionNetV3, MobileNet, and EfficientNet B1. The development of this architecture took place within the areas of classification and hyperparameter learning. In contrast to the other eight architectures, the MobileNet architecture exhibits the lowest computational performance and highest accuracy, according to the comparison results. By employing the confusion matrix for evaluation, an accuracy of 82.7% is achieved. Modified MobileNet has the best speed because it keeps a lower-computation architecture and cuts down on unnecessary pre-processing. This means that a lot of people can use smartphones with more realistic data conditions to make it work.

Keywords: *mushroom; deep learning; modified mobilenet; classification*

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1. Introduction

Mushrooms are an extremely diverse group of organisms that inhabit a wide variety of ecosystems [1]. There are applications for certain mushrooms in the pharmaceutical, biotechnology, and food industries. Mushrooms are also capable of producing hazardous poisonous compounds for both humans and animals [1], [2]. The process of distinguishing between poisonous and non-poisonous mushrooms is critical for preserving ecosystems, human health, and safety [2]. Deep learning is the method approach that is most frequently implemented [1], [3].

Poisonous mushrooms, when consumed, may contain harmful compounds such as aflatoxin, muscarine, or amatoxin, which can cause life-threatening poisonousness. Public, scientific, and agricultural stakeholders must be able to identify poisonous mushrooms to prevent potential hazards [2]. Distinguishing poisonous mushrooms from non-poisonous mushrooms is a formidable task that necessitates considerable expertise. In addition, the variability of colour, size, and shape of mushrooms renders manual identification more challenging and less dependable. [2], [4]. For this reason, the development of more precise and efficient mushroom identification techniques is crucial. One potential technological approach is deep learning.

Deep learning, which falls under the category of artificial intelligence (AI), has exhibited remarkable aptitudes in the identification of patterns within image data [4]-[7]. Deep learning can be employed in this particular context to analyze mushroom images and discern distinctive attributes that distinguish poisonous mushrooms from non-poisonous mushrooms. This encompasses attributes such as the design, hue, consistency, and even minute details of the mushroom crown.

The utilization of deep learning in the identification of mushrooms facilitates the extraction of crucial attributes from mushroom images, while also mitigating noise and enhancing image quality [1], [8]. The deep learning methodology was trained to identify patterns and distinguish between poisonous and non-poisonous mushrooms with a high degree of accuracy and at a reduced cost to duplicate knowledge. Furthermore, deep learning can be employed to analyze mushroom

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images and identify distinctive patterns that differentiate poisonous from non-poisonous mushrooms [2]. This can facilitate the development of automated systems that the general public can employ to proactively mitigate potential hazards.

Deep learning is being used a lot for image classification. This research encompasses a variety of disciplines. CNN employs deep learning to classify faces and other ethnicities through a comparison of the MobileNet v1, MobileNet v2, VGG16, VGG19, ResNet-50, and MobileNet v2 architectures [9]. 95% accuracy is achieved with MobileNet v1 [9]; this is the highest level of accuracy. CNN research utilizing the ResNet-50 architecture model can also be used to classify images captured by camera devices utilized to detect protected animals, fingerprints, cervical cancer, and diseases affecting robusta coffee leaves. [10]-[13]. Miranda et al. conducted a comparative analysis of classification outcomes and the benefit of Contrast Limited Adaptive Histogram Equalization (CLAHE) on image quality. The findings indicate that the implementation of CLAHE in fingerprint classification can enhance accuracy by 11.79%, or 95.05% [10]. The demonstrated accuracy results for camera trap image classification were as follows: testing accuracy of 90.43% and training accuracy of 99.34% [11]. When it comes to the stage of cervical cancer image classification, ResNet50 and ResNet101 are compared. ResNet50 has an accuracy of 91%, while ResNet101 achieves an accuracy of 89% [12]. Resnet50 is considered an ancient and superior architecture in comparison to more recent ResNet architectures, including ResNet101. When it comes to the classification of cervical cancer, it is not always the case that more recent architectures are superior to earlier ones [12]. The accuracy for classifying maladies affecting robusta coffee leaves was 92.68% for the binary class and 88.98% for the multiclass case [13]. By integrating CNN with the VGG-19 architectural model, researchers have achieved a classification accuracy of 93.18% for maladies affecting rice plants [14]. The Random Forest algorithm was employed to classify the Caltech-101 dataset with an achieved accuracy of 93.73% [15]. DenseNet-201 architectures for image classification are also extensively implemented [16]. A comparison was made between the accuracy of the DenseNet-121, DenseNet-169, and DenseNet-201 architectures to classify multiple sclerosis. The findings indicate that DenseNet-201 exhibits the highest level of accuracy, reaching 98.31% [16]. In addition, a comparison is made between CNN architectures DenseNet121, DenseNet169, and DenseNet201 in the context of COVID-19 detection and the classification of chest x-ray images. Additionally, the outcomes demonstrate that DenseNet121 achieves an optimal accuracy of 95.2% [17]. The classification of lung cancer utilizing InceptionNet-V3 yielded an accuracy of 98.96% [18]. Comparing the EfficientNet and MixNet architectures yields fruit classification results, with EfficientNet B1 achieving the highest accuracy of 100% [19]. Leaf maladies in plants are also categorized utilizing the EfficientNet architecture. Architectures EfficientNetB0-B7, AlexNet, ResNet50, VGG16, and Inception V3 were compared in the course of this investigation [20]. The results on EfficientNet show a 99.97% accuracy [20]. The performance value of 60.20 per cent [21] is achieved when the EfficientNet architecture is utilized for image and video segmentation processes in endoscopic disease detection.

Previous research [1], [4], [22], and [23] have investigated the classification of mushroom images utilizing CNN architecture. Previous research employed a total of nine distinct mushroom species, which were subsequently classified into two categories: non-poisonous and poisonous [1]. MobileNetV2, ResNet50, and VGG19 comprise the architecture. Nevertheless, the dataset utilized in Haksoro's study was obtained from Kaggle. A significant number of preprocessing steps were applied to the dataset, including square compression, augmentation, and normalization of the pixel intensity value data. It has a pixel value range of 0 to 2. By employing MobileNetsV2 [1], this study achieved a comparatively elevated accuracy rate of 92.19%. Shiitake mushrooms were categorized into two distinct groups in real-time by Liu et al. [4]: those with smooth caps and those with flower caps. Due to the direct nature of data collection in this study (angle, lighting conditions, physical vibrations, etc.), the resultant dataset contained a great deal of noise. The outcomes of R-CNN, YOLOv3, YOLOv4, SSD 300, and YOLOX were compared in this study. Using the YOLOX algorithm yields an accuracy of 98.10 per cent, according to the results. [4]. Deep learning [22] is utilized in the study of the categorization of mushrooms into two distinct groups: poisonous and non-poisonous. A random selection of 45 mushroom species from the internet comprised the dataset for this investigation. The obtained mushroom images are subsequently enhanced through a preprocessing phase of the dataset. A great deal of disturbance and a variety of sizes and colours are present in the randomly acquired dataset. The preprocessing phase of this study involved the implementation of CLAHE (Contrast Limited Adaptive Histogram Equalization). Training and testing data are compared in a ratio of 80:20. InceptionV3, VGG16, and Resnet50 are the CNN architectures that are compared in this study. With 88.40% accuracy, InceptionV3 produced the most accurate results [22]. The utilization of CNN [23] enabled Wu et al. to distinguish between poisonous and non-poisonous mushroom species. This research utilizes mushroom images from Kaggle to compile its dataset. Decontaminating contaminated data and eliminating image backgrounds are the preprocessing steps performed to enhance the quality of mushroom images. Thus, according to this study, MobileNetV2 achieves the highest accuracy at 81.25

per cent [23]. Another study divided mushrooms into six groups based on their genus using CNN [24]. These groups were Boletus (not poisonous), Boletus (poisonous), Ganoderma (not toxic), Ganoderma (poisonous), and Russula (not poisonous). There are two dropout layers, three convolution layers, and three MaxPooling layers in the model used in the study. The goal of dropout is to keep the model from being too well-fitted. Rotation, zoom, flip, width shift, height shift, shear, and resize are some of the preparation steps used in this study. This model was most accurate when it was trained (89%) and tested (82%). In another study [25], it was possible to divide mushrooms into five groups using CNN and R-CNN. There are 623 images of mushrooms grouped into non-poisonous and poisonous types. The background of the mushroom pictures in the dataset used in this study was taken out before it was used. Therefore, the dataset is of very high standard. AlexNet, ResNet-50, and GoogLeNet are the designs that are being compared. When CNN and R-CNN were used to classify mushrooms, the suggested model showed 98.50% and 95.50% accuracy, respectively.

The majority of mushroom classification datasets are acquired from Kaggle, where they are consistently provided with high-quality data. Furthermore, prior investigations have commonly employed stacked and high-level preprocessing techniques to enhance the image quality. The dataset utilized in this study was collected via the crawling technique and requires minor pre-processing. Data testing in real time may become more challenging as the classification procedure becomes progressively more time-consuming due to excessive preprocessing. This is due to the extremely high variation in mushroom images during real-time implementation testing.

The investigation is driven by the following motivations and contributions: Investigate architectures that show positive results in dealing with sample variations under real-world conditions by employing crawling techniques that require minor pre-processing; Look for a lightweight architecture so that it can be implemented more widely.

The contributions are made in light of the aforementioned gaps: Evaluating the performance and accuracy of the architecture using a more genuine sample dataset obtained from the internet via crawling techniques without any pre-processing; Developing classification performance results with the proposed architecture and hyperparameters with good performance and lower complexity for wider implementation.

2. Research Methods

The design and hyperparameters used in this study will be tested on a private dataset. The elements were found by crawling through info on the internet. This project aims to collect a wider range of mushroom image data so that the study can be carried out with less pre-processing. This research came up with eight sets of designs and hyperparameters that could be used to group different kinds of mushrooms into different groups. The eight designs are MobileNet, EfficientNet B1, VGG16, VGG19, EfficientNet201, and DenseNet121. This building shows how architecture has changed from the previous architectural style to the newer style. During this research, classification and hyperparameter divisions were made better. The best architecture will be picked from the different options, and it will then be the subject of a more in-depth study and discussion.

The way of mushroom classification used in this study is shown in Figure 1.

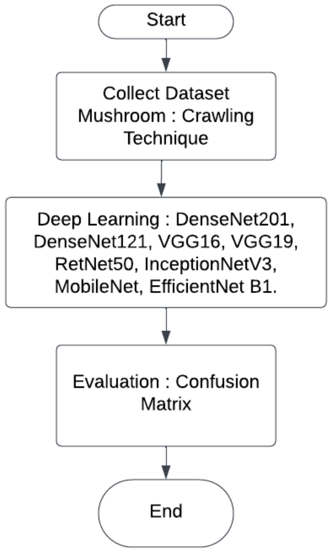


Figure 1. Flowchart System of Mushroom Classification

2.1 Dataset

The information used in this study was obtained through the mining process, which involved using Python code in Google Colab. There are 643 image records of poisonous and nonpoisonous mushroom types. A dataset is made through a crawling technique that contributes variety to the data that needs to be classified during both the training and validation stages. For keyword-based picture queries, crawling methods that work with both English and Indonesian are used. This is because records found using Indonesian language indexing methods are not very good. A lot of pictures that didn’t belong were found. Then, an English-language crawling process was used to add an average of 100 images of each type of mushroom to the collection. Some of the mushroom images that are put out are ones of mushroom dishes that don’t show the characteristics of the mushroom. Therefore, the goal of a wider application in the real world using a variety of dataset types is reached. Table 1 has a lot of different types of images.

The way of collecting the dataset using the crawling technique produced random pictures of mushrooms that showed big differences between types of mushrooms (Table 1). Deep learning is then used to process the collected information without any preprocessing. Because too much preprocessing could make the classification process take longer, this study aims to be used in real-life and practical situations so that it can deal with the different aspects of mushroom images.

Table 1. Dataset of Mushroom

Mushroom Names	Mushroom Pictures	Types of Mushrooms
Destroying Angels		Poisonous
Conocybe Filaris		Poisonous
Death Cap		Poisonous
Enoki		Non-Poisonous
Champignon		Non-Poisonous
Maitake		Non-Poisonous
Oyster		on-Poisonous

The information used in this study is split into three separate sets: training, validation, and testing. 70% of all the data is used for training, 20% for validation, and 10% for testing.

2.2 Deep Learning Architectures for Classification

In this study, 8 different types of deep learning models were used. The most accurate results were found when these designs were used on datasets with a lot of different types of data. The MobileNet architecture is usually the one picked. Compared to other designs, this one has lighter computing. This is to make it easier for more people to use smartphones in real life. Figure 2 shows more information about the design that was used in this study. The MobileNet architecture comprises multiple essential layers, including convolutional, pooling, flattening, fully connected, and dropout layers. For this research, ImageNet weights were employed. Our analysis and experiments involved augmenting the network with pairs of fully connected and pooling layers, tailored to accommodate seven classes. The determination of the optimal number of output neurons was achieved through empirical trials, ultimately leading to the selection of 512 neurons for our desired outcome.

Table 2 shows an explanation of the hyperparameters that were used. Hyperparameters are used in all eight of the suggested architectures. The testing process produced hyperparameters that contributed to good performance results.

Table 2. Hyperparameter Deep Learning

Parameter	Value
Batch size	32
Epoch	150
Optimizer	Adam
Learning rate	lr = 1e-4
Decay	decay = 1e-6
Data Split	70:20:10 (training, testing, validation)
Activation function	Sigmoid
Loss	Categorical cross-entropy

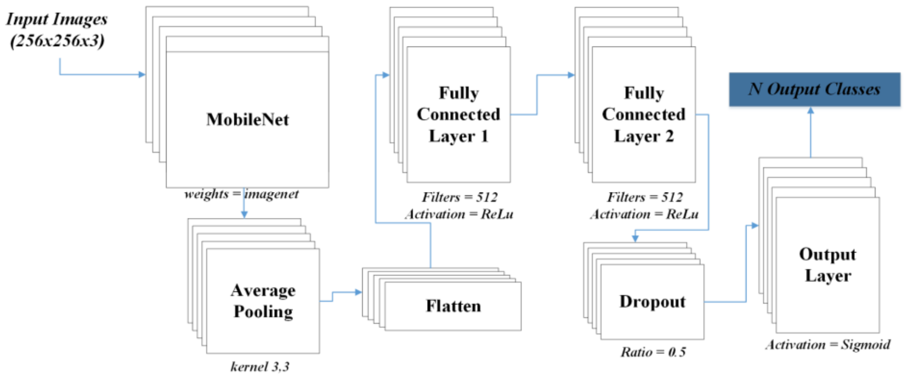


Figure 2. Proposed Architecture and hyperparameter at Modified MobileNet

2.3 Evaluation

In this study, the confusion matrix was used to figure out how to rate the results of the mushroom classification. Using a confusion matrix along with multiclass can help create the best design for sorting different types of mushrooms. The design description of the confusion matrix table can be found in Table 3.

Table 3. Confusion Matrix

		Predicted	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

Based on Table 3, the confusion matrix can be used to measure the performance of mushroom-type classification results by calculating accuracy, precision, and recall values.

For this study, the dataset is randomly split into 70 parts for training, 20 parts for validation, and 10 parts for testing. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are used to figure out the matrices [26]. Some of these are F1-Score, accuracy, recall, and precision. The mathematical models for each of these success metrics are shown in Formula 3 through 6.

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$F1\ Score = \frac{2\,(Precision)(Recall)}{Precision+Recall} \quad (6)$$

3. Results and Discussions

The objective of this study is to identify a lightweight architecture that exhibits optimal performance in the classification of poisonous and non-poisonous mushrooms. Dataset challenges for the eight proposed architectures consist of datasets that are more realistic or prevalent in the natural world, as well as minimal preprocessing of the datasets.

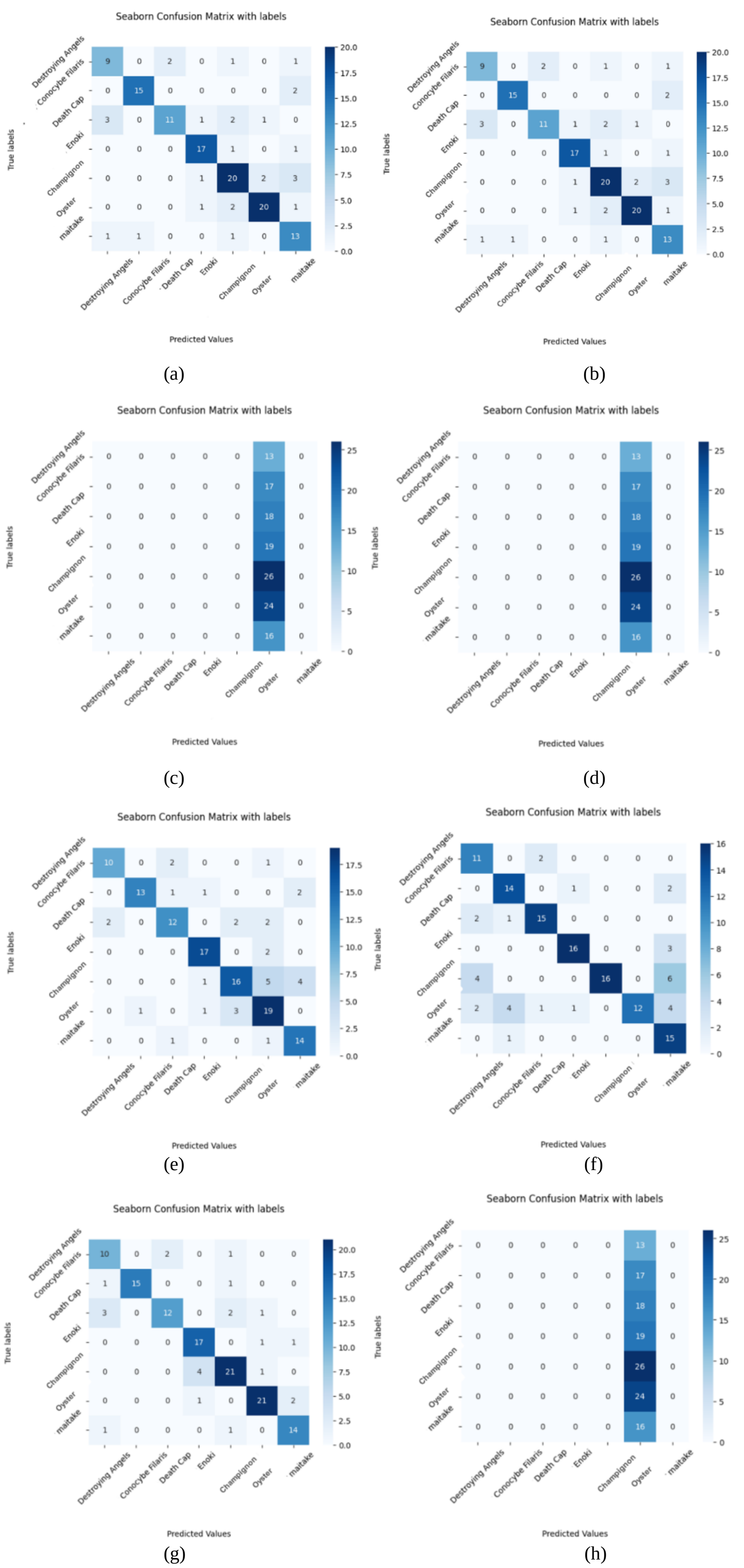
3.1 Performance Comparison Between Architectures

An assessment utilizing the confusion matrix reveals that, in comparison to other evaluated architectures, the proposed MobileNet architecture and hyperparameters exhibit the most efficient performance and require the least amount of computation. This architecture is the answer to two things proposed as a contribution, namely, an architecture that has smaller parameters than other architectures. In contrast, this architecture exhibits superior accuracy performance in comparison to alternative architectural designs. Comparisons of performance are detailed in Table 4.

The evaluation of performance is conducted by utilizing a confusion matrix. Several indicators commonly employed in this context include precision, recall, accuracy, and the F1 score. The primary metric utilized is accuracy performance.

Table 4. Performance Comparison on Tested Architecture

Architecture	Training Accuracy (%)	Loss Training	Validation accuracy (%)	Loss Validation	Precision (%)	Recall (%)	Accuracy (%)	F1 Score (%)
DenseNet201	100	0,0001	86,79	0,5535	79,4	78,5	78,9	78,4
DenseNet121	99,79	0,0080	85,91	0.5331	79,4	78,5	78,9	78,4
VGG16	18,28	1.9390	15,09	1.9463	2,6	14,3	18	4,4
VGG19	18,28	1.9394	0.1509	1.9453	2,6	14,3	18	4,4
ResNet50	100	4.3133e-05	0.7925	1.1588	78	76,8	75,9	76,8
InceptionNetV3	99,16	0.0726	0.6981	2.7527	78,6	77,1	74,4	74,6
MobileNet	1.00	4.7824e-05	0.4987	0.8868	82,9	82,4	82,7	82,3
EfficientNet_B1	97,48	0.1051	0.1509	4.3273	0.026	0.143	0.180	0.044



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 3. Evaluation results using confusion matrix (a) DenseNet201, (b) DenseNet121, (c) VGG16, (d) VGG19, (e) ResNet50, (f) InceptionNetV3, (g) MobileNet, (h) EfficientNet B1

Table 4 shows that MobileNet has the highest amount of accuracy. After this, DenseNet201, DenseNet121, and ResNet50 do the same thing. It is interesting to note that the latest version, EfficientNet B1, is surprisingly less effective than older ones. When the situation and hyperparameters of the case are taken into account, that architecture is used to solve the case study. Besides these things, MobileNet is an architectural system that can effectively handle extra computing resources. Putting it into action on cell phones and smartphones, which are commonplace right now, is possible and needs fewer resources for a wider reach. Destroying Angels mushrooms (poisonous), enoki mushrooms (non-poisonous), and Champignon (non-poisonous) yield the least accurate confusion matrix results when the mobileNet architecture is applied; each of these mushroom types has a five-point indicator of prediction error. Figure 3 shows the results of the full assessment that were obtained by using the confusion matrix. Table 4 uses the confusion matrix to compare several evaluation results from the eight architectures.

3.2 Computing

In addition to looking at performance results, this research also compares how well different architectures work computationally. The total number of parameters in MobileNet is about 5592775, which is about 21.33 MB. This is less than the total number of parameters in the other eight tried and changed architectures. Table 5 has information that is specific to comparisons. The number of parameters for each architecture is shown in Table 5. These numbers came from the proposed architecture that we put into action in Google Colab using the model. summary() command.

Table 5. Computational Comparison Between Architectures

Architectures	Total Parameter
DenseNet201	22520903 (85.91 MB)
DenseNet121	9401415 (35.86 MB)
VGG16	159267631 (607.56 MB)
VGG19	21339719 (81.40 MB)
ResNet50	28048775 (107.00 MB)
InceptionNetV3	23118119 (88.19 MB)
MobileNet	5592775 (21.33 MB)
EfficientNet B1	9463438 (36.10 MB)

4. Conclusions

It is the goal of this study to find a lightweight architecture that works with more implementations. It uses less computing power and a more real dataset, like one that was gathered outside of a lab or in the real world. The results show that the modified MobileNet approach succeeds in over the other two methods. This is because it is more accurate and uses less computer power. Researchers can use the results of this study to make useful apps, like smartphone apps that can spot mushrooms in real-time from pictures taken by users. This will help people who like nature, farmers, and everyone else learn how to tell the difference between dangerous and non-poisonous mushrooms that exist in nature.

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