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Performance Enhancement of Mushroom Species Classification via Modified InceptionV3

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Abstract

Mushrooms encompass a very large number of species, and some of them are toxic to humans. It is very difficult to classify mushroom species quickly and accurately, especially for common individuals who often encounter wild mushrooms in nature. To address this problem, this study envisioned an automated mushroom species classification system using deep learning methods and the InceptionV3 model. This model was chosen because it is highly generalizable, performs well with challenging images, and is precise for most image-based classification tasks. The dataset comprises 18 mushroom species and was created from a Kaggle version. Data balancing, preprocessing, data augmentation, and model training constitute the research work. The dataset has been divided into 70% training, 15% validation, and 15% test. The training results show that the model achieves 81.35% accuracy in identifying mushroom species. The study contributes to the development of AI-based image recognition technology that can help humans find mushrooms more rapidly and securely.

Keywords: *Mushroom Identification, InceptionV3, Deep Learning, Wild Mushrooms, Artificial Intelligence.*

1 Introduction

Mushrooms, highly diverse organisms, play important roles in ecosystems as decomposers and food sources. Some types of mushrooms, however, are poisonous and can cause serious health problems or even death if accidentally consumed. Because many species have significant morphological similarities, distinguishing between safe-to-eat and poisonous mushrooms is very difficult [1]. To identify toxicity, people often use traditional methods, such as observing rice color changes or using silver spoons when boiling mushrooms. However, these methods are not accurate and cannot be relied upon as scientific references [1].

In Gujarat, India, wild mushrooms are abundant across various ecosystems, including forests, agricultural fields, and farmer pathways. Through morphological observations and taxonomic classification, the research successfully identified at least 57 mushroom species [2]. However, manual identification requires considerable time and special skills, making it generally difficult to implement. These limitations indicate that more effective and accessible methods for mushroom identification are needed. Consequently, contemporary technology can play an important role in addressing this issue.

The image-based object identification process has become more efficient and accurate with the development of artificial intelligence, particularly in computer vision. Deep learning methods based on Convolutional Neural Networks (CNNs) have proven effective across many applications, including plant disease classification, vegetable classification, skin cancer detection, and face mask usage

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detection. Previous researchers have developed CNN-based and vision transformer automatic classification systems to identify wild mushrooms in mycology. With support from community science data, a system called Fungivision can achieve classification accuracy of nearly 93% [3].

More advanced CNN architectures, such as InceptionV3, offer advantages in terms of computational efficiency, accuracy, and stability on smaller datasets. To improve generalization capability and accelerate training, this model uses auxiliary classifiers, batch normalization, and convolution factorization [4]. Additionally, InceptionV3 has demonstrated outstanding performance across various domains. For example, in fashion product image classification, this model can achieve an accuracy score of 92.86% and an F1-score of 92.85% on data with high visual similarity between classes [5]. InceptionV3 successfully completes challenging picture classification tasks that require the model to discern large visual changes between classes, as demonstrated by Maryamah et al. [5]. These techniques seem to have great potential to improve the accuracy and efficiency of mushroom classification systems.

However, a thorough analysis of the current research literature identifies several gaps. The model's capacity to generalize to a wider range of species and visual situations is constrained by prior research using deep learning on fungal species, which frequently concentrates on a small number of classes [6] or makes use of fewer datasets. Importantly, many studies' use of transfer learning is not adequately tuned, leading to very accurate models that are not resilient to strong visual similarity across certain classes. Furthermore, a thorough per-class study that could identify specific visually challenging species is often absent from the debates, which tend to focus solely on overall accuracy.

2. Research Method

2.1 Research Workflow

The purpose of this research is to create an automatic classification system that can identify mushroom types. Deep learning methods and the InceptionV3 model were chosen because of InceptionV3's ability to handle images with high complexity and provide very good results for image-based classification tasks. This research aims to create a system that can automatically identify and classify mushroom species with a high level of accuracy. The dataset used consists of 18 mushroom species, covering various types of wild mushrooms with variations in morphology and color. The research methodology is illustrated in Figure 1.

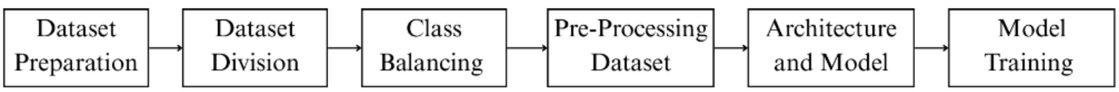

Figure 1 Research Workflow of the Proposed Mushroom Classification System

2.2 Data Collection

This research began by analyzing the Kaggle mushroom image dataset at https://www.kaggle.com/datasets/iftekhar08/mo-106?select=MO_94. This research used a dataset of about 18 different mushroom species, each with significant visual variations. The dataset of 5,526 images spanning 18 mushroom species plays an important role in developing an accurate automatic classification system. The distribution of images across 18 mushroom species is shown in Figure 2.

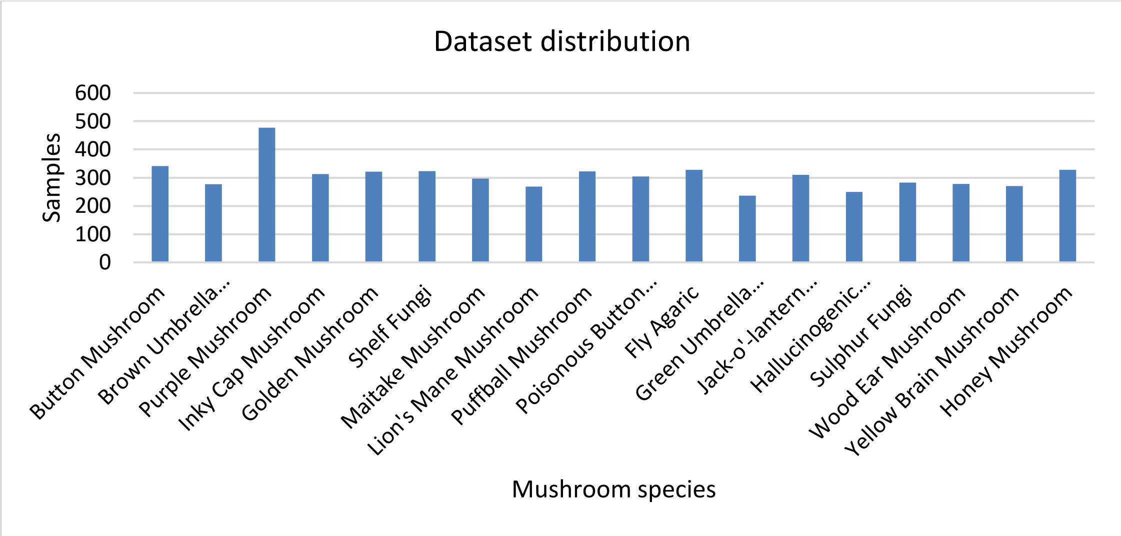

Figure 2 Class Distribution

The number of samples collected for each species varied, with some species having more images than others. Purple Mushroom has 477 images, while Honey Mushroom has 328 images. According to previous research, bias in the classification process can be caused by an imbalance in the distribution of sample numbers between species [7]. The existence of possible representation bias between classes, which can affect model accuracy, is indicated by this significant variation in the number of samples. Additionally, this imbalance indicates differences in image-taking conditions, where each species has different visual attributes, such as size, shape, and color, which can affect the model's ability to identify mushrooms correctly [3].

Figure 3 Dataset Visualization

Three subsets were created from the entire dataset, comprising 4,248 samples from 18 different species: 70% for training (about 2,974 samples), 15% for validation (about 637 samples), and 15% for testing (about 637 samples). This partitioning ratio, which maximizes training data while preserving enough independent data for trustworthy model evaluation, is a conventional approach [8], [6].

Stratified splitting was used to provide a proportionate and balanced representation of each species in the training, validation, and testing sets due to the varied morphology and intrinsic imbalance in the number of samples between species. This crucial step improves the model's capacity to generalize to new, unknown data by reducing the possibility of bias and preventing the model from overfitting to the majority classes [9]. The 4,248 samples were systematically divided into three groups, with 70% going toward training and 15% going toward testing and validation, as shown in Figure 4. The structured distribution that was employed to get the data ready for the classification model is validated by this graphic representation.

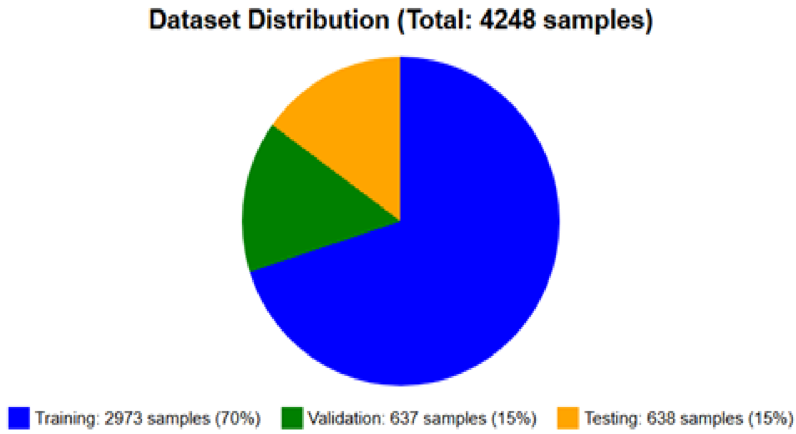

Figure 4 Dataset Separation

2.3 Class Balancing

The quality of the dataset in the process of mushroom image classification using deep learning is very important for the success of the model. Some mushroom species may have very different numbers of image samples, which can cause an imbalance in data distribution between classes. This can cause bias during the model training process, which can reduce the accuracy and generalization ability of the classification system.

As shown in Figure 5, which illustrates dataset balancing. In this research, class balancing was carried out to overcome the imbalance in the distribution of the number of images between species in the dataset. The imbalance in the number of images between classes can cause the model to be more likely to prioritize classes that have more images, which can affect classification accuracy in underrepresented classes [10]. Therefore, class balancing was carried out by adjusting the number of images in each class to achieve the smallest possible number, 236.

The mushroom image dataset was divided into training, validation, and testing sets at the pre-processing stage. This dataset is then ready to be used in model training. The first step in the pre-processing process is to reduce the size of the images. All images were resized to 224 x 224 pixels. This was done to ensure the input required by the InceptionV3 model, which requires uniform image sizes so that the architecture can process them well. Additionally, image pixel values were normalized by dividing them by 255, so that pixel values were in the range between 0 and 1. The purpose of this normalization is to speed up the training process by keeping input values stable and avoiding too large scale differences between feature values [11]. To enhance the dataset and reduce the possibility of overfitting, the training set was augmented with data. Several augmentation techniques include image rotation, horizontal flipping, zooming, and contrast changes. This augmentation improves the model's ability to better classify mushrooms in various conditions, such as variations in lighting, position, and viewpoint, because it helps it find more varied patterns in the images. Improving model generalization and expanding data diversity are the goals of this augmentation.

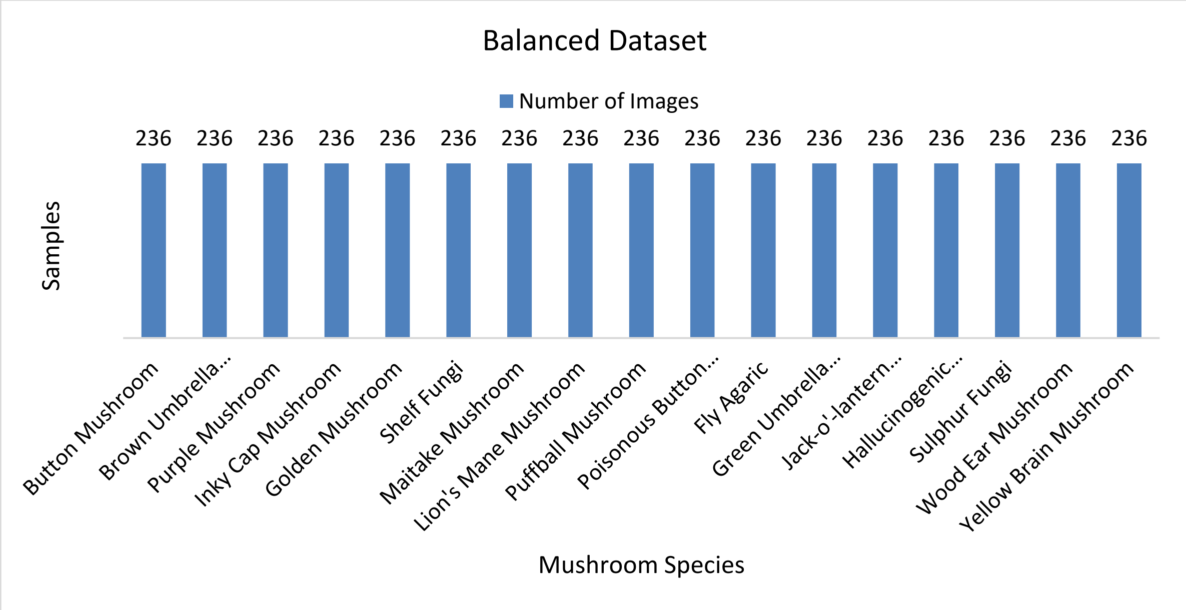

Figure 5 Balanced Dataset Visualization

Using the 'KerasImageDataGenerator' library, a rigorous data augmentation method was implemented to further improve the dataset and reduce the risk of overfitting. A rotation range of up to 45 degrees, width and height shifts of 0.35, and shear and zoom transformations of 0.35 and 0.4, respectively, were among the augmentation approaches. To account for illumination fluctuations, brightness adjustments ranging from 0.6 to 1.4 were applied in addition to horizontal and vertical flips. These techniques work especially well for enhancing model generalization in datasets with intricate morphological structures, as those present in a variety of mushroom species[12].

One of the main problems in pre-processing mushroom datasets is maintaining the unique information of each species. The 224 x 224 pixel size was carefully chosen to balance computational needs and the depth of visual information. Machine learning algorithms can converge more quickly and stably with normalization by dividing by 255. This is very important considering the extraordinary morphological diversity of the mushroom collection being studied. The purpose of this comprehensive preprocessing approach is to turn raw datasets into the best representations for machine learning analysis. Each step, from measurement to enhancement, is intended to gather and enhance visual information that will be used by the model for the mushroom species classification process.

2.4 Architecture and Model

The Convolutional Neural Network (CNN) InceptionV3 architecture was used in this research. Using techniques such as factorized convolution, auxiliary classifiers, and label smoothing, this CNN is known to be capable of handling deep learning-based image classification [13]. In this research, the transfer learning approach is very important, where the model uses initial weights that have been trained on the ImageNet dataset [14]. The transfer learning process allows the model to use common features that have been learned from the reference dataset, which is very helpful in extracting complex visual patterns in mushroom images [15].

A partial fine-tuning approach was used during the model optimization stage. The top 30% of the base model layers were made trainable, but the first layers were kept frozen to maintain general feature extraction skills acquired from ImageNet. This particular threshold was selected to prevent catastrophic forgetting or overfitting while enabling the model to adjust its high-level convolutional filters to the distinctive morphological features of the mushroom species. This approach finds a compromise between applying domain-specific adaptation and utilizing pre-trained information. Similar methods have proven effective in existing studies, such as the implementation by Hadi, which utilized fine-tuning on the DenseNet model to yield superior results in specialized image classification tasks [16].

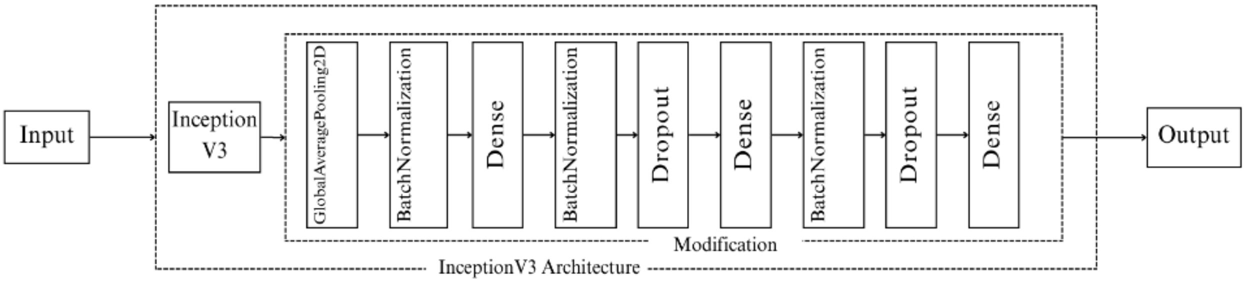

Figure 6 Modification of the InceptionV3 architecture

As illustrated in Figure 6, the InceptionV3 architecture was modified to optimize feature extraction for the specific task of mushroom classification. Convolutional layers for fundamental feature capture and inception modules that execute simultaneous convolutions at many scales make up the base model [17]. In order to analyze the complicated cap structures, colors, and surface textures of different mushroom species, these modules must be able to capture multi-level visual data, including edges, textures, and complex patterns [17], [18].

A specially created classifier head was incorporated using the underlying InceptionV3 architecture to improve the classification performance. In particular, a 2D Global Average Pooling layer processes the high-dimensional output from the base model to reduce spatial dimensions while preserving important information. Two fully connected Dense layers with 512 and 256 neurons, respectively, come next. To speed up convergence and guarantee training stability, both layers include Batch Normalization with the ReLU (Rectified Linear Unit) activation function. A dropout rate of 0.001 was used to reduce overfitting and preserve the model's effectiveness. This is an important tactic for preserving generalization ability in complicated datasets [19], [20].

To ensure reproducibility, a strict setup was used during training. In order to balance computational speed and gradient update quality, the model was trained for 50 epochs using a batch size of 32 [21]. To provide consistent, if slow, convergence, we used the Adam optimizer with a learning rate of 0.0001 [18]. In addition, a number of callback strategies were used, including ReduceLROnPlateau to dynamically modify the learning rate when convergence slows down, ModelCheckpoint to maintain the best-performing weights, and EarlyStopping to avoid overfitting [17]. Batch normalization, in conjunction with this thorough setup, ensures the model remains stable while detecting the notable visual differences in the mushroom dataset.

3 Results and Discussions

3.1 Accuracy and Loss

The training process of the InceptionV3 model for mushroom classification shows interesting and complex machine learning dynamics. The model experienced a significant learning curve during the initial training stage, with validation accuracy of only 19.3% and training accuracy of 43.9%. This initial lack of accuracy indicates the complexity of the mushroom classification task, which includes understanding diverse and complex visual patterns. During training, the model showed remarkable adaptability and extraordinary learning speed. The rapid increase in accuracy demonstrates the InceptionV3 architecture's ability to extract important features from mushroom images. As illustrated in the accuracy and loss graph in Figure 7.

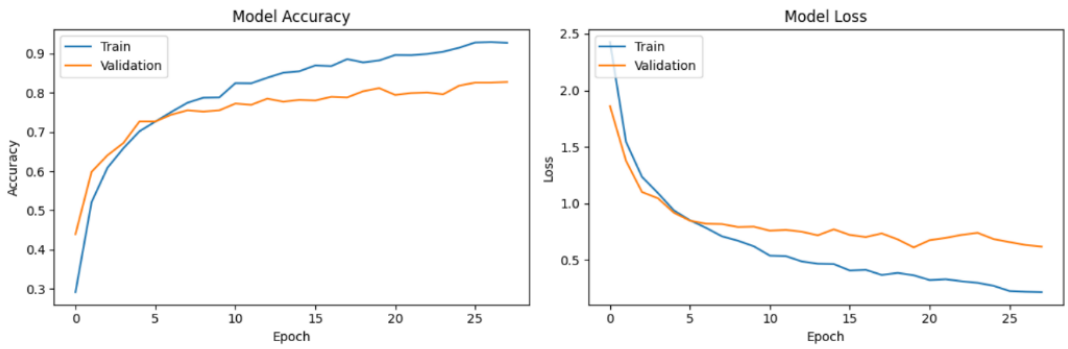

Figure 7 Accuracy and Loss Graphic

At the 28th epoch, the model reached its optimal point with the highest training accuracy of 92.7% and the highest validation accuracy of 82.7%. The difference between validation and training accuracy shows a good balance in the learning process, with minimal indications of overfitting. The accuracy curve shows a stable pattern, with a validation accuracy range of 75-81%, even as training accuracy increases. This stability shows the model's broad generalization ability, where the model understands general mushroom classification patterns and not just memorizes training data. One sign that effective transfer learning and data augmentation methods are the model's ability to maintain consistent validation accuracy.

Analysis of loss values provides additional information about how the model learns. Training loss started at 2.89 at the beginning of the course and gradually decreased. This gradual decrease indicates that the model systematically improves its predictions, reducing classification errors with each iteration. The lowest training loss rate, 0.2137, was achieved at the 28th epoch. This indicates a very low error rate. The validation amount also dropped from 1.86 at the first epoch to 0.6180 at the peak, following a similar pattern. If there is the same decrease in training and validation, it indicates good convergence. In this situation, the model can reduce errors on the training data and make accurate generalizations on previously unseen data.

In addition, Table 1's comparison, which shows a distinct performance difference between the Basic InceptionV3 and the Modified InceptionV3 models, bolsters the accuracy and loss trends. The Modified InceptionV3's overall accuracy of 81% is a considerable improvement above the Basic model's 72%. Both the weighted-average F1-score, which goes from 0.72 to 0.81, and the macro-average F1-score, which rises from 0.71 to 0.81, consistently show this improvement. These findings show that improved classification ability across all mushroom classes is directly related to the noted decrease in loss during training.

Table 1 Comparison Between Basic InceptionV3 and InceptionV3 Modified

Types of Mushroom	Basic InceptionV3				InceptionV3 Modified			
	Precision	***Recall***	***F1-Score***	***Support***	***Precision***	***Recall***	***F1-Score***	***Support***
Golden	0.63	0.60	0.62	20	0.75	0.75	0.75	20
Hallucinogenic	0.58	0.58	0.58	33	0.79	0.79	0.79	33
Jack-o'-lantern	0.70	0.86	0.78	22	0.94	0.68	0.79	22
Button	0.54	0.54	0.54	26	0.79	0.73	0.76	26
Poisonous Button	0.66	0.63	0.64	30	0.79	0.73	0.76	30
Flat Wood	0.80	0.83	0.82	24	0.84	0.88	0.86	24
Rainbow Ear	0.92	0.85	0.88	40	0.78	0.90	0.84	40
Fly	0.82	0.97	0.89	34	0.89	1.00	0.94	34
Honey	0.46	0.53	0.49	30	0.67	0.67	0.67	30
Maitake	0.89	0.81	0.85	31	0.97	0.94	0.95	31
Butter	0.69	0.93	0.79	29	0.74	0.86	0.79	29
Brown Umbrella	0.55	0.58	0.56	19	0.78	0.74	0.76	19
Green Umbrella	0.59	0.57	0.58	46	0.71	0.80	0.76	46
Puffball	0.84	0.72	0.78	29	0.88	0.72	0.79	29
Sulfur Mold	0.90	0.51	0.65	35	0.88	0.66	0.75	35
Lion's Mane	0.97	0.91	0.94	33	1.00	0.97	0.98	33
Tint	0.76	0.83	0.79	23	0.83	0.83	0.83	23
Purple	0.65	0.67	0.66	36	0.75	0.86	0.81	36
Overall Accuracy	**0.72**				**0.81**			
Macro Average	**0.71**				**0.81**			
Weighted Average	**0.72**				**0.81**			

The Modified InceptionV3 shows significant accuracy gains for a number of species at the class level. While Poisonous Button Mushroom improves from 64% to 76%, Button Mushroom accuracy rises from 54% to 76%, suggesting improved differentiation of visually similar groups. Additionally, improvements are seen in Hallucinogenic Mushroom from 58% to 79% and Golden Mushroom from 62% to 75%. Fly Agaric accuracy rises from 89% to 94%, and Maitake Mushroom accuracy rises from 85% to 95% for classes that already perform well, demonstrating that the redesigned architecture not only lowers misclassification in challenging classes but also improves predictions in visually unique species.

3.2 Confusion Matrix

Confusion matrix analysis shows complex variants in the performance of the InceptionV3 model on 18 different mushroom species. One of the main problems in mushroom classification is the high range of accuracy (63%-94%) and loss range (6%-53%). Each mushroom species has different morphological diversity, colors, and structures, which causes this complexity. Large variations in classification performance indicate that even with an advanced deep learning architecture, not all mushrooms have the same easily recognizable visual features. These differences indicate the complexity of the mushroom world and the limitations of the model. As shown in Table 2, the accuracy and loss results for each class.

Table 2 Accuracy and Loss for Each Class

No.	Mushroom Classes	Accuracy (%)	Loss (%)
1	Golden Mushroom	78	22
2	Hallucinogenic Mushroom	75	25
3	Jack-o'-lantern Mushroom	84	16
4	Button Mushroom	75	25
5	Poisonous Button Mushroom	71	29
6	Shelf Fungi	92	08
7	Wood Ear Mushroom	89	11
8	Fly Agaric	94	06
9	Honey Mushroom	65	35
10	Maitake Mushroom	85	15
11	Butter Mushroom	91	09
12	Brown Umbrella Mushroom	80	20
13	Green Umbrella Mushroom	79	21
14	Puffball Mushroom	82	18
15	Sulphur Fungi	63	37
16	Lion's Mane Mushroom	89	11
17	Inky Cap Mushroom	78	22
18	purple mushroom	87	13

Some species show remarkable ability for classification, with Fly Agaric being the most prominent. This model can identify the unique characteristics of this mushroom with almost perfect precision, with 94% accuracy and 6% loss. Very different visual features, such as striking colors or different structures, are what most likely contribute to this success. Shelf Fungi have an accuracy of 92% and 91%, respectively, showing that the InceptionV3 model is very good at capturing complex morphological features. The success of classification in these species shows that the InceptionV3 model is very good at capturing complex morphological features. In contrast, species that are much more difficult to classify, such as Sulphur Fungi and Honey Mushrooms, have accuracy of 63% and 65%, respectively. This difficulty indicates the difficulty of distinguishing species with comparable or less clear visual characteristics.

An in-depth analysis of the confusion matrix reveals informative classification error patterns in the InceptionV3 model. The confusion matrix shows that the visual characteristics of some mushroom species are very similar. As a result, the model tends to misclassify certain species. For example, with an error rate of 87.6%, Sulphur Fungi are often classified as Jack-o'-lantern Mushrooms. This indicates that both species have significant visual features, such as color, structure, and surface texture. The complexity of these classification errors indicates a major difficulty in distinguishing mushroom species with similar morphology. Understanding the limitations of deep learning-based classification systems is very helpful because the model's ability to find these error patterns itself.

Additionally, classification error patterns show a hierarchy of visual proximity between mushroom species. Some species pairs show a higher tendency for this cross-classification, which can be considered an indication of morphological proximity. For example, there is a possibility of classification errors in species with similar characteristics, such as Golden Mushrooms and Honey Mushrooms. Additionally, there is a possibility of errors between Sulphur Fungi and Jack-o'-lantern Mushrooms. The high frequency of these errors indicates the very subtle complexity of the mushroom world, not a weakness of the model. The InceptionV3 model shows the limitations of visual discrimination between species and finds visual nuances that are almost invisible to the human eye. Thus, analyzing the confusion matrix enhances scientific understanding of mushroom classification and also measures model performance.

3.3 Model Performance

This subsection describes the performance of the InceptionV3 model in classifying 18 mushroom species using accuracy, recall, and F1-Score metrics. A comprehensive analysis of these metrics shows the complex nuances of model performance that go beyond simple accuracy. The accuracy of the model in classifying a class, namely the proportion of correct positive predictions, is called precision. This research found that Fly Agaric and Lion's Mane Mushroom have the highest accuracy levels, reaching 0.941, indicating that the model's predictions for this class are very reliable. Conversely, Shelf Fungi has the lowest accuracy of 0.825, indicating larger positive errors. Recall assesses the model's ability to find all instances of a class. As shown in Table 3.

Table 3 Model Performance

No.	Mushroom Class	Precision	Recall	F1-Score	Support
1	Golden Mushroom	0.781	0.781	0.781	32
2	Hallucinogenic Mushroom	0.889	0.750	0.814	32
3	Jack-o'-lantern Mushroom	0.867	0.842	0.853	38
4	Button Mushroom	0.648	0.750	0.696	32
5	Poisonous Button Mushroom	0.707	0.707	0.707	41
6	Shelf Fungi	0.825	0.917	0.868	36
7	Wood Ear Mushroom	0.886	0.886	0.886	44
8	Fly Agaric	0.941	0.941	0.941	34
9	Honey Mushroom	0.652	0.652	0.652	23
10	Maitake Mushroom	0.967	0.853	0.906	34
11	Butter Mushroom	0.857	0.909	0.882	33
12	Brown Umbrella Mushroom	0.804	0.804	0.804	41
13	Green Umbrella Mushroom	0.756	0.790	0.772	43
14	Puffball Mushroom	0.861	0.816	0.838	38
15	Sulphur Fungi	0.679	0.633	0.656	30
16	Lion's Mane Mushroom	0.914	0.889	0.901	36
17	Inky Cap Mushroom	0.842	0.780	0.810	41
18	purple mushroom	0.742	0.867	0.800	30

An interesting pattern is shown by recall, which assesses the model's ability to find all instances of a class. With the highest recall of 0.909, Butter Mushroom became the most prominent class, showing that the model successfully identified most of the specimens of this class. Conversely, Sulphur Fungi has the lowest recall of 0.633, indicating that the model has difficulty finding all instances of this class. High internal variability, limited sample sizes in the dataset, or significant morphological complexity are among the reasons recall rates are low. F1-Score, which is the harmonic mean of precision and recall, provides a balanced assessment of classification performance. With the highest F1 score of 0.941, fly agaric outperforms again, followed by jack-o'-lantern mushroom with a score of 0.853, showing consistency in the model in classifying certain species.

Recall, which assesses the model's ability to find all instances of a class, shows an interesting pattern. With the highest recall of 0.909, Butter Mushroom became the most prominent class, indicating that the model successfully found most of the specimens of this class. Conversely, Sulphur Fungi has the lowest recall of 0.633, indicating that the model has difficulty finding all instances of this class. Low recall percentages can be caused by high internal variables, sample limitations in the dataset, or significant morphological complexity. F1-Score, which is the harmonic mean of precision and recall, provides a balanced assessment of classification performance. Fly agaric has the highest F1 score, 0.941, and jack-o'-lantern has a lower score, 0.853, indicating the model's consistency in classifying certain species.

Analysis of support reveals an important dimension in the distribution of mushroom classification datasets, with the number of samples per species varying significantly from 23 to 44. Rainbow Ear Mushroom has the largest collection with 44 samples, while Honey Mushroom has the smallest with only 23 examples, which could affect the classification model's performance. This imbalance creates methodological challenges, where species with limited samples face more complex representation difficulties in the machine learning process. To overcome these limitations, the research implemented data augmentation techniques, such as image rotation, horizontal flipping, and contrast adjustments, enabling the model to explore broader visual variations. Transfer learning with the InceptionV3 model trained on the ImageNet dataset plays a crucial role in overcoming sample limitations, enabling the model to leverage common features learned from large datasets to better generalize to relatively small mushroom datasets.

3.4 Prediction Results

The classification results are displayed. This gives a clear picture of how the InceptionV3 model identifies mushroom species. Examples of successful and unsuccessful classifications are shown in the image. This provides direct evidence of the model's strengths and weaknesses. Examples of successful classifications show a very accurate model, with some species found with almost perfect confidence. For example, golden mushrooms are identified with 99.6% confidence, indicating that the model is very precise in identifying this species. This success demonstrates the model's ability to extract highly distinctive visual features. As shown in Table 4.

Table 4 Mushroom Species Prediction Results

No.	Mushroom Species	Actual Class	Predicted Class	Confidence
1	Golden Mushroom	Golden Mushroom	Golden Mushroom	99.6%
2	Sulphur Fungi	Sulphur Fungi	Jack-o-lantern	87.6%
3	Poisonous Button Mushroom	Poisonous Button Mushroom	Poisonous Button Mushroom	98.8%
4	Golden Mushroom	Golden Mushroom	Golden Mushroom	87.5%
5	Butter Mushroom	Butter Mushroom	Butter Mushroom	99.9%

Interesting patterns emerged in the classification process during a thorough analysis of the prediction results. Butter mushrooms were categorized with 99.9% confidence, indicating that the model can recognize this species with almost perfect precision. However, this research also found some classification error cases that provide important information. One of the most interesting examples is the error in classifying Sulphur Fungi. The model with 87.6% confidence misidentified the species as Jack-o'-lantern Mushrooms. This error is not just a weakness of the model, but it also shows the morphological complexity of mushrooms that are very similar visually. This shows an important problem in mushroom classification, where differences between species can be very subtle and difficult to distinguish.

Classification error cases provide significant understanding of the limitations and possibilities of deep learning models in species identification. For example, Poisonous Button Mushrooms were found with 98.8% confidence. This shows the model's ability to identify complex visual details of various types of mushrooms. However, differences in confidence between species indicate that not all mushrooms have the same visual features. Certain species have prominent features, while other species require more careful examination. This phenomenon demonstrates the extraordinary morphological diversity of mushrooms, with each species having a unique visual signature. The InceptionV3 model classifies and explains the visual complexity of various mushroom species.

The results go far beyond simple classification. There is a lot of potential in fields such as mycology, conservation, and food safety because of the model's ability to distinguish species accurately. However, classification errors indicate the importance of additional validation and caution. Although deep learning models are very helpful in species identification, they should not be considered a source of absolute truth. To achieve the most accurate and reliable mushroom classification, this research emphasizes that a collaborative approach that combines artificial intelligence with mycological expertise is urgently needed.

3.5 Comparison with Baseline Architectures

Two prominent baseline Convolutional Neural Network (CNN) architectures, VGG16 and MobileNetV2, were used in a comparative experiment on the same mushroom dataset in order to confirm our architectural choice and support the changes made. Table 5 provides a succinct presentation of the comparison's findings. According to the overall accuracy data, the InceptionV3 Modified model outperformed both MobileNetV2 (80.6 %) and VGG16 (76.1%), achieving an overall accuracy of 81.3%. This result provides empirical evidence that InceptionV3 is the best architecture for classifying mushroom species in this dataset.

Table 5. Comparison with Baseline Architectures

Model	**Accuracy (%)**
VGG16	76.1
MobileNetV2	80.6
Modified InceptionV3	81.3

The strong performance of InceptionV3, especially when compared to VGG16 and MobileNetV2, stems directly from its unique Inception Module architecture. This module is expertly designed to process convolutions simultaneously across various spatial scales. This capacity to handle multiple scales is particularly vital for classifying mushrooms, given their considerable visual variability in size, placement, and intricate physical characteristics. In contrast, VGG16's architecture, which relies on sequential filter operations, proved less effective at capturing this broad range of multi-scale features, resulting in its lowest accuracy. While MobileNetV2 offers excellent computational efficiency through its *Depthwise Separable Convolution*, its accuracy was slightly below that of InceptionV3. This suggests that for classification tasks demanding fine-grained feature resolution and the ability to differentiate subtle distinctions between species, InceptionV3's emphasis on high-quality multi-scale feature extraction ultimately delivers a more effective and optimal classification outcome.

3.6 Comparison with Previous Research

This study of mushroom classification using the InceptionV3 model offers a new perspective in the development of artificial intelligence-based mushroom species recognition technology. This research achieved an overall accuracy of 81.3% in classifying 18 mushroom species, which places it in a competitive position in the current research landscape. This method stands out compared to previous research, especially in terms of dataset complexity and techniques used. Previous research, such as that conducted by Picek et al., used a combination of Convolutional Neural Network (CNN) and Vision Transformer with 80.45% accuracy, but only used a few species. The difference in this accuracy does not necessarily make the research conducted less important. On the contrary, this difference provides a deeper understanding of the complexity of mushroom classification. Table 6 is attached to provide a more comprehensive context about research on mushroom classification.

Table 6 Comparison with Previous Researches

Researches	Method	Number of Species	Accuracy	Main Approach
Proposed method	InceptionV3	18	81.3%	Transfer Learning
Picek et al (2022) [3]	CNN + Transformer	1604(DF20 Dataset)	80.45% (VIT)	Hybrid Model + ViT
I'itsyam et al (2023)[21]	CNN	8	95%	CNN

Compared to earlier techniques, this method offers significant advances, especially in balancing accuracy with realistic deployment considerations. Using a complex combination of Convolutional Neural Network (CNN) and Vision Transformer architectures, Picek et al. achieved 80.45% accuracy on their large Danish Fungi 2020 dataset, which included 1,604 species. Although their hybrid model produced remarkable results, it needed human validation and extensive metadata integration. A standard CNN approach was utilized in another study by I'itsyam et al. [21] that focused on 8 different kinds of mushrooms and reported a 95% accuracy for edible/poisonous classification.

The comparison provides valuable information regarding the compromises in fungal classification schemes. With a much simpler architecture and less auxiliary data, our InceptionV3 model achieves similar accuracy to the more complicated system of Picek et al [3]. The 81.3% accuracy is a well-balanced option that is easier to implement in field settings while maintaining respectable performance. For cases where expert validation or metadata gathering may not be feasible, this is especially helpful. It is important to view the variations in accuracy among studies as reflections of the different aims and limits of each study context rather than as limitations. Our method specifically addresses the need for medium-scale, realistic classification systems that don't require a lot of infrastructure to implement.

This study's thorough examination shows how deep learning models can be successfully modified for fungus classification tasks. We have created a system that achieves acceptable accuracy while remaining usable for researchers and practitioners with limited computational resources by focusing on transfer learning with InceptionV3. This is a significant step in expanding the availability of AI-based fungus recognition for field applications, citizen science initiatives, and ecological research.

3.7 Discussion

Research on mushroom classification using the InceptionV3 model presents a comprehensive analysis that goes beyond mere image classification, revealing fundamental complexities in AI-based mushroom species identification. The model's performance variation across species reflects unique challenges in visually interpreting organisms with highly diverse morphology. Fly Agaric, with an accuracy of 94%, and Shelf Fungi at 92%, demonstrate the model's capability to extract highly distinctive visual features. In contrast, Sulphur Fungi with 63% accuracy and Honey Mushroom at 65% highlight the model's limitations in discriminating between species with more subtle visual differences.

The applied transfer learning methodology demonstrates an innovative approach to overcoming the limitations of domain-specific datasets. By leveraging general knowledge from the ImageNet dataset, the model was able to transfer generic features to the very specific context of mushroom classification. This process is not just a technical adaptation, but a sophisticated representation of how deep learning can cross knowledge domain boundaries. Data augmentation techniques such as image rotation, horizontal flipping, and contrast adjustments play a crucial role in expanding the visual representation space, allowing the model to explore complex morphological variability. Confusion matrix analysis reveals classification error patterns that are far more complex than mere algorithmic inaccuracies. The error in classifying Sulphur Fungi as Jack-o'-lantern Mushrooms is not just a technical weakness, but a reflection of deep biological complexity. Mushroom species have very subtle visual nuances, almost indistinguishable even by the trained human eye. This indicates that mushroom classification is not just a matter of pattern recognition techniques, but also an epistemological challenge in understanding the morphological diversity of nature.

The methodological implications of this research are significant for the development of deep learning technology. The InceptionV3 model is not just a classification tool, but a representation of a new computational approach in understanding biological diversity. The model's ability to capture very complex visual nuances shows the potential of deep learning in transforming the way we categorize and understand species diversity. This approach opens new opportunities in various fields, from mycology and conservation to computational taxonomy. However, this research also critically explores the limitations of the deep learning approach. The variability in performance between species reveals the inherent complexity in visual-based classification. Factors such as color variation, growth structure, ecological context, and mushroom developmental stages create complex methodological challenges. The InceptionV3 model has successfully demonstrated the ability to capture some of this complexity, but it also underscores the need for more sophisticated approaches.

Data augmentation strategies have significant potential to expand the model's generalization capabilities. By manipulating images through rotation, flipping, and contrast adjustments, this research demonstrates how deep learning models can be enriched to capture broader visual variability. This approach not only improves accuracy but also provides insights into how computational systems can learn to see through various perspectives. The main challenges identified include morphological complexity across species, limitations in dataset representation, subtle visual nuances, and internal variability within each species. Going forward, further research should focus on developing more adaptive model architectures, expanding datasets with broader species coverage, integrating mycological expert knowledge, and exploring cutting-edge deep learning techniques to capture greater visual complexity.

The ethical and practical context of this research is also worth considering. Although automatic classification systems have significant potential in helping mushroom identification, this research firmly emphasizes that deep learning technology should not be considered an absolute source of truth. Ongoing validation, collaboration with domain experts, and multidisciplinary approaches remain key in developing reliable and meaningful species identification technology. Fundamentally, this research is not just about mushroom classification, but about how artificial intelligence can help us understand the complexity and diversity of life. The developed InceptionV3 model serves as a window to see how computational technology can translate the visual diversity of nature into understandable knowledge constructs.

4. Conclusion

In this research, a mushroom classification system using the InceptionV3 model has been successfully developed, achieving an overall accuracy of 81.35% and capable of automatically classifying 18 mushroom species. Through transfer learning and data augmentation approaches, the model manifested special abilities in recognizing mushroom species with significant variations in performance between species: highest accuracy up to 94% achieved for Fly Agaric and Shelf Fungi, while facing the greatest challenges with Sulphur Fungi and Honey Mushroom, with accuracy of 63-65%. Therefore, this research represents a significant contribution displayed in the field of mushroom recognition technology using deep learning. This generation solution offers a significantly faster, more accurate, and safer way to identify mushrooms, which enables it to be used in subsequent mushroom classification projects using deep learning techniques.

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