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RESEARCH ARTICLE

Mushroom Species Classification in Natural Habitats Using Convolutional Neural Networks (CNN)

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ABSTRACT Mushrooms are known for their significant nutritional value and are essential to the human diet. However, the dilemmas associated with ingesting poisonous mushroom species stress the critical need for accurate identification methods. Despite many efforts to identify mushroom species, these methods are often limited in identifying them from their natural habitat. This study addresses this gap by presenting a computer vision approach that uses machine learning for accurate and reliable image-based classification of mushrooms from their natural habitat. The proposed solution aims to enhance the safety of mushroom consumption by precisely classifying mushroom species. The images of mushroom species are taken from their natural habitat to increase their applicability in real-world scenarios. The study proposed Convolutional Neural Network (CNN) models and different image augmentation techniques to accurately identify one hundred and three (103) mushroom species. Evaluation of the model from the 20% of the test dataset showed an accuracy of 96.70% and high precision-recall and F1 score for each mushroom class. The study achieved a 4.4% increase in accuracy from the state-of-the-art approaches in mushroom species identification. This research is significant to mycologists, scientists, and the general public in promoting the safe usage of mushroom species.

INDEX TERMS Mushroom, deep learning, classifications, convolutional neural network (CNN).

I. INTRODUCTION

Mushroom is biologically part of the fungal kingdom, contributes to numerous ecological procedures, and holds considerable importance in the human diet and medication. A mushroom is a macro fungus with a fruiting body visible to the naked eye and belonging to the family *Agaricaceae*. The mushrooms differ in colors, shapes, surfaces, and size [1].

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There are different species of mushrooms with different morphological characteristics. Identification of mushroom species is a very important but challenging task. There is a need for a solution to accurately identify the mushroom species from their natural habitat to promote their safe usage,

Mushrooms are low in calories, fat, sodium, and cholesterol and rich in nutrients like selenium, niacin, vitamin D, potassium, proteins, and fiber [2]. They help treat illnesses such as Alzheimer's, Parkinson's, stroke risk, and hypertension [3]. Mushrooms offer health benefits like anti-inflammatory, anti-cancer and cholesterol-lowering properties [4]. Mushrooms are a culinary staple worldwide, adding unique flavors and nutritional value to dishes [5].

The commercial mushroom industry has grown due to rising demand. Mushrooms have a long history of cultural importance to Greeks, Romans, and Chinese, who valued mushrooms for their health benefits [6], [7], [8]. Europe consumes an average of 3.5 kilograms of mushrooms annually, with its market estimated to reach a Compound Annual Growth Rate (CAGR) of 8.07% between 2017 and 2023 [9]. The mushroom consumption is estimated to reach 20.84 million tons, with a CAGR of 6.41% [3], [9]. China's edible mushroom production exceeds 40 million tons, worth 346.5 billion Yuan, ranking fifth in the agriculture sector [10].

Mushrooms are classified into three main fungal groups: *Zygomycetes*, *Ascomycetes*, and *Basidiomycetes* [11]. Earth has an estimated 150,000 to 160,000 mushroom species, with edible varieties comprising only a small fraction. Approximately 2,000 species are considered edible, and around 700 have reported medicinal properties [12]. Of the identified species, about 25% are edible, 50% are poisonous, 20% may have health effects, approximately 4% are seemingly safe but potentially risky, and the remaining 1% are highly dangerous [13]. Therefore, accurate identification of mushroom species is essential for their safe and practical use.

Numerous mushroom species have different uses and distinct appearances [14]. The resemblance in color and shape of mushroom species makes it challenging to identify them based on apparent symptoms [14]. Accurate classification is vital to differentiate edible species from poisonous ones [15]. Various approaches are used in current research for mushroom classification, which is important but challenging due to the large number of species with overlapping shapes and colors.

Classifying mushroom species is crucial due to the significant risk posed by toxic mushroom varieties that resemble edible ones. With an estimated two to three million mushroom species, the potential for misidentification can lead to serious health issues [16]. Traditional methods for mushroom identification are labor-intensive and often misleading [17]. Distinguishing mushroom species involves an examination of morphological characteristics such as stem size, cap diameter, and color [18]. Identification of mushroom species is challenging due to overlapping morphological characteristics of mushroom species. Manual expertise is used to identify mushroom species using the physical characteristics of mushroom species. Existing methods of identification of experts face limitations, such as high labor demands and susceptibility to human error.

Machine learning has a significant role in every aspect of life [19], [20]. Deep learning applications have a revolutionary role in agriculture to improve productivity [20], [21], [22]. Recent technological advancements in machine learning offer promising solutions for improving mushroom classification based on visual characteristics. These algorithms can effectively analyze thousands of images, significantly enhancing the speed and accuracy of identification compared to traditional methods [23].

Current research indicates that integrating machine learning helps in accurate identification and facilitates mushroom classification and analysis, which is important for enhancing safety in mushroom consumption [5], [24]. Convolutional Neural Networks (CNN) have revolutionized image-based classification for various problems [25], [26]. CNN has shown remarkable potential in automatically extracting complex information from images, thereby improving the precision and productivity of image identification [27]. They are particularly well-recognized for identifying complex visual traits in mushroom images. CNN models consist of convolution layers for feature extraction and pooling layers for spatial hierarchy [14]. CNN is revolutionary in mycology by providing unparalleled precision in image-based mushroom identification and classification. Numerous mushroom species have created new research opportunities by automatically learning and extracting characteristics from various datasets.

The development of machine learning in mycology signifies a paradigm shift, overcoming past constraints and presenting a bright future for mushroom identification [28]. This research explores the CNN potential to enhance the efficiency and accuracy of mushroom species classification. This study aims to improve and accelerate the classification procedure with CNN, making it more effective for researchers and mycologists. This study aims to classify mushrooms accurately, providing precise predictions for each image and handling dissimilarities in mushroom outline, style, texture, and other features to address this issue. The aim is to build a CNN-based model capable of distinguishing mushroom species. This CNN model will be trained and evaluated based on the precise classification of mushroom species. The following are the major objectives of the study.

1) To configure and train a CNN model for accurately classifying one hundred and three (103) mushroom species using images from their natural habitats.
2) To explore image preprocessing techniques, such as resizing, cropping, and augmentation and CNN model configurations to enhance the model's performance in accurately identifying mushroom species.

This study significantly contributes to fungal species identification by addressing the complexity arising from many species sharing similar characteristics, especially shape and color. Recognizing the importance of accurate classification in mushroom species identification, this study presents an innovative approach using CNN. The main goal is to overcome the accuracy limitations of current identification methods. The developed machine learning model is designed to classify mushrooms based on various features such as contour, style, and texture, effectively considering changes in appearance. The intended success of this project will result in a CNN-based model that enables careful identification of fungal species, minimizes classification errors, and ensures reliable results for fungal classification. This paper contributes to the scientific understanding of fungal identification and presents practical solutions to address critical needs in this field. The key contributions of this paper are as follows:

1) Developed a CNN model for accurate and reliable classification of one hundred and three mushroom species based on mushroom images from their natural habitat.
2) Explored image preprocessing techniques such as resizing, cropping, and augmentation to improve model performance in accurately identifying many mushroom species from natural habitats.
3) Explored the CNN model attributes and hyperparameters to extract and analyze complex visual structures for accurate mushroom species identification from thier natural habitat.

This work follows a structured approach, with a literature review in the next section covering background research and providing historical context and related theories. The literature review establishes the conceptual foundation and identifies research gaps. The research methodology is explained in detail in the **Materials and Methods** section, elaborating on the proposed solution and describing its conceptualization, system architecture, and main features. The **Results** section presents the experimental results and evaluation metrics. The **Discussion** section explores the implications and suggests avenues for future research. Finally, the **Conclusion** section is provided.

II. RELATED WORK

This section explores deep learning applications in mycology, offering a thorough review of applications proposed to improve the accuracy and efficiency of mushroom identification. By examining current research, techniques, and technical advancements, this section critically reviews the existing state of knowledge, identifying gaps and limitations in current methodologies and setting the stage for the proposed research work.

Zahan et al. [13] recommended a mushroom classification model using a deep learning model to distinguish edible and poisonous mushrooms. The proposed methodology is based on improving the image quality using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method with the InceptionV3 model. The proposed InceptionV3 achieved an accuracy of 88.40% in identifying different mushroom classes. Preechasuk et al. [18] proposed a CNN model for classifying forty-five types of mushrooms to enhance the safe usage of mushrooms. The proposed model achieved precision, recall, and F1 scores of 0.78, 0.73, and 0.74, respectively.

Cong et al. [9] proposed Shiitake mushroom detection using YOLO v3 with GhostNet16 as the backbone and incorporating spatial pyramid pooling and an adaptive feature pyramid network to enhance detection accuracy. The proposed model achieved a mean average precision (mAP) of 97.03%, outperforming the original YOLO model by 2.04%.

Wang et al. [29] proposed an automated mushroom grading system based on mushroom pilus size using image processing techniques. Using the watershed method, the system used image processing to measure the pileus diameter for accurate mushroom sorting. The proposed grading method achieved 97.42% accuracy.

Lu and Liaw [30] proposed a marker-controlled watershed algorithm combined with Otsu threshold and morphological operations to accurately segment and recognize *Agaricus bisporus* mushrooms from a complex background in real-time. The proposed algorithm achieved a 95.7% recognition accuracy.

Ketwongsa et al. [16] proposed mushroom classification using the deep learning approaches of CNN and Regional CNN (R-CNN) to distinguish edible and poisonous mushrooms. The study also compared the performance of the AlexNet, ResNet-50, and GoogLeNet in mushroom identification. The study focused on reducing the training and evaluation time without sacrificing accuracy. The proposed model achieved 98.50% accuracy using CNN and 95.50% accuracy using R-CNN. Subramani et al. [31] proposed mushroom image classification using deep learning approaches to differentiate the toxic and non-toxic mushroom species. The study evaluated the performance of the Support Vector Machine (SVM), ResNet50, YOLO V-5 and AlexNet. The SVM outperformed the evaluated models with 83% accuracy in recognizing the toxic and nontoxic mushrooms. Yağmur Demirel and Demirel [23] explored the performance of different CNN architectures for mushroom species classification. The evaluation of different CNN architectures revealed that the MobileNetV2-based model outperformed in mushroom classification with training accuracy of 99.99%, validation accuracy of 97.20%, and test dataset accuracy of 97.89%. Ketwongsa et al. [16] proposed YOLOX-based identification of Shitake mushroom quality to enhance mushroom picking efficiency. The proposed YOLOX model was built by transfer learning and optimized using a high-efficiency channel pruning mechanism to recognize mushroom quality. The proposed model proved to be very effective in recognizing mushroom texture with a mAP value of 99.96%.

Wang [32] proposed a deep learning pipeline (ViT-L/32) approach for the identification of poisonous mushrooms after applications of image pre-processing techniques like image argumentation. The proposed approach of mushroom identification achieved 95.97% accuracy from the test dataset. Guo [33] proposed a Deep Sparse Dictionary Learning (DSDL) approach of mushroom image classification using deeper feature extraction through stack autoencoder. The sparse dictionary learning loss functions enhanced the feature learning process and showed excellent performance in mushroom image classification. Lee et al. [34] proposed a CNN model to classify mushrooms from field-collection images to assist non-expert users in identifying poisonous mushrooms. The proposed solution showed high precision and recall in mushroom classification. Fadlil et al. [35] proposed mushroom identification through image feature extractions. The process involves segmenting and converting mushroom images into grayscale. The extracted features are classified using an Artificial Neural Network (ANN) with 93% accuracy.

Ketwongsa et al. [16] compared the performance of three pre-trained models, AlexNet, ResNet-50, and GoogLeNet, for classifying five species of mushrooms. The proposed deep learning model improved classification accuracy while reducing training and testing time. The AlexNet model achieved the highest accuracy of 98.50% in the identification of edible and poisonous mushroom species.

Zhu et al. [36] proposed MobileNetV3 deep convolutional network model for Shiitake mushroom quality classification using a hybrid dataset and advanced techniques like data augmentation, SE module enhancement, and transfer learning to achieve high accuracy in complex backgrounds. The proposed MobileNetV3 model achieved a recognition accuracy of 99.91%.

Liu et al. [37] developed a deep learning model for quality classification of shiitake mushrooms using the YOLOX algorithm. The model effectively identified and graded mushroom quality with a mAP of 99.96% and reduced the model size by over 50%. Wang [32] proposed an automatic mushroom species classification model for food-borne disease prevention using the Vision Transformer (ViT).

Rahman et al. [26] proposed the classification of pathogenic fungi from microscopic images using the CNN model. The study explored the performance of different CNN variants for filamentous fungi identification. The evaluation of the different variants of the CNN model revealed that the DenseNet CNN model achieved the highest accuracy of 65.35%. Zhao et al. [25] proposed VGG16, ResNet18, and GoogLeNet models for wild mushroom classification by collecting wild mushroom data from multiple natural scenes. The study applied a bagging algorithm for enhanced accuracy. The proposed solution also applied ensemble learning to adapt to complex recognition scenes for wild mushroom classification. The evaluations showed that the ensemble learning approach using VGG16, ResNet18, and GoogLeNet models achieved 93.1% accuracy in identifying wild mushrooms.

Serhat et al. [28] proposed CNN and transfer learning-based approach to classify 77 fungus species to prevent poisoning from consuming toxic fungi. Kiss and László [38] explored different learning approaches for classifying mushroom images using CNN models. By using different learning approaches like incremental-size learning, gradual freezing, transfer learning, and model size, the proposed approach achieved 92.6% accuracy in the classification of a large number of mushroom species.

Farokhah et al. [39] proposed eight deep learning architectures for the classification of mushrooms, named Modified DenseNet201, DenseNet121, VGG16, VGG19, ResNet50, InceptionNetV3, MobileNet, and EfficientNet-B1. After evaluating the models, the result showed that the MobileNet architecture had the lowest computational performance but achieved the highest accuracy at 82.7%. Özbay et al. [40] developed a CNN model based on multi-feature fusion for mushroom species classification. The model enhances feature extraction by combining CNN with a meta-heuristics-based optimization approach. They report significant improvements in the classification of mushrooms.

Rani et al. [41] proposed transfer learning and stacked ensemble approaches of mushroom classification. The study assessed the performance of individual transfer learning approaches and stacking ensemble techniques for mushroom classification. The stacking ensemble approach using the weighted average method of ResNet50V2-MobileNet–VGG16 outperformed with an accuracy in the range of 90.54% - 98.42% in mushroom classification. Peng et al. [42] proposed model of poisonous wild mushroom classification using a combination of attention and convolutional networks (ConvNets). The performance of the proposed M-ViT model assessed on two datasets revealed an accuracy of 96.21% and 91.83%. The proposed approach outperformed the individual advanced ConvNets and attention networks approaches of mushroom species classification. A summary of existing approaches to mushroom species identification is given in Table 1.

Recent studies have explored CNN and many other deep-learning approaches for mushroom species identification from natural habitat images. Various CNN architectures and training strategies have been investigated, with models achieving high accuracies [14], [25], [26], [28], [38]. It is observed that various artificial intelligence technologies-based applications were proposed to classify mushroom species. These proposed solutions are limited to identifying edible mushrooms matching their color, shape, and structure. Datasets used in existing research also have limited scope and range in terms of number of mushroom species. The existing literature is limited in terms of the number of species identified. It is also very important to recognize the mushroom species in their natural habitat, which is also limited in existing literature. There is a need to explore the possibility of identifying many mushroom species from images of their natural habitat.

III. MATERIALS AND METHODS

The study intends to explore the performance of the CNN model in identifying images of many mushroom species taken from their natural habitat. This section describes the dataset, data preprocessing, dataset splitting, model architecture, and model evaluations to serve the study's objectives. The flow chart of the methodology is shown in Figure. 1. The algorithm for data pre-processing, CNN model training and evaluation is given by Algorithm 1.

TABLE 1. Summary of literature review.

Ref.	Methodology	Results	Limitation
[9]	Shiitake mushroom detection using YOLO V3, GhostNet16, Spatial Pyramid Pooling, Adaptive Feature Pyramid Network	mAP: 97.03%	Limited to Shiitake mushroom.
[13]	Mushroom classification (edible vs. poisonous) using CLAHE and InceptionV3	Accuracy: 88.40%	Requires larger datasets.
[16]	Edible and poisonous mushroom classification using CNN and R-CNN	CNN: 98.50%, R-CNN: 95.50%	Limited to five mushroom species
[18]	Classifying 45 mushroom types using CNN	Precision: 0.78, Recall: 0.73	Limited mushroom species.
[23]	Mushroom species classification using MobileNet-V_2	Accuracy 90%	Accuracy need to improve
[29]	Automated mushroom grading using image processing and watershed method	Accuracy: 97.42%	Only grading of fresh white button mushrooms
[30]	Agaricus bisporus mushroom recognition and Marker-controlled watershed algorithm	Accuracy: 95.7%	Limited species grading
[31]	Toxic and non-toxic mushroom classification using SVM, ResNet50, YOLO V5, AlexNet	SVM: 83% accuracy	Low accuracy
[32]	Mushroom species classification using (CNN) and region convolutional neural network (R-CNN)	98.50% and 95.50%	Limited species.
[33]	Poisonous mushroom identification using ViT-L/32	Accuracy: 95.97%	Limited to eleven mushroom species
[35]	CNN for categorizing mushrooms from field-collection images	89%	Limited mushroom species
[36]	Mushroom identification using ANN with feature extraction	Accuracy: 93%	Limited mushroom species

TABLE 1. *(Continued.)* Summary of literature review.

Ref.	Methodology	Results	Limitation
[37]	Shiitake mushroom quality classification using MobileNet-V_3 and transfer learning	Accuracy: 99.91%	Limited to Shiitake mushroom
[32]	Shiitake mushroom quality classification using YOLOX algorithm	mAP: 99.96%	Limited to Shiitake mushroom species
[39]	Mushroom classification using different deep learning architectures	MobileNet: Accuracy: 82.7%	Limited mushroom species
[41]	Poisonous wild mushroom classification using M-ViT, ConvNets, attention networks	Accuracy: 96.21%, 91.83%	Accuracy needs to enhance

A. DATASET

The mushroom dataset used in this study contained one hundred and three classes of mushroom species images taken from Kaggle [43]. The images of different types of mushroom species were from their natural habitat. The distribution of edible and poisonous mushroom species in the dataset is given in Table. 2. The status of each mushroom species related to edible (E) or poisonous (E) is given in Table. 3. The The images of some mushroom species from their natural habitat are shown in Figure. 2.

TABLE 2. Distribution of dataset.

Mushroom Category	Number of Mushroom species
Edible	34
Poisonous	69

B. DATA PREPROCESSING

The mushroom images were processed before they were used in training and evaluating models. The pre-processing of mushroom images aimed to streamline the model training process to increase the accuracy of machine-learning models in mushroom classification. The mushroom species names were encoded to class labels to facilitate the model training process. Table. 3 gives the mushroom species class labels. The dataset images of mushroom species were pre-processed in the following ways;

1) **Resizing:** Images in a dataset were in various sizes. Each image in the dataset was made to the same size in 128×128.

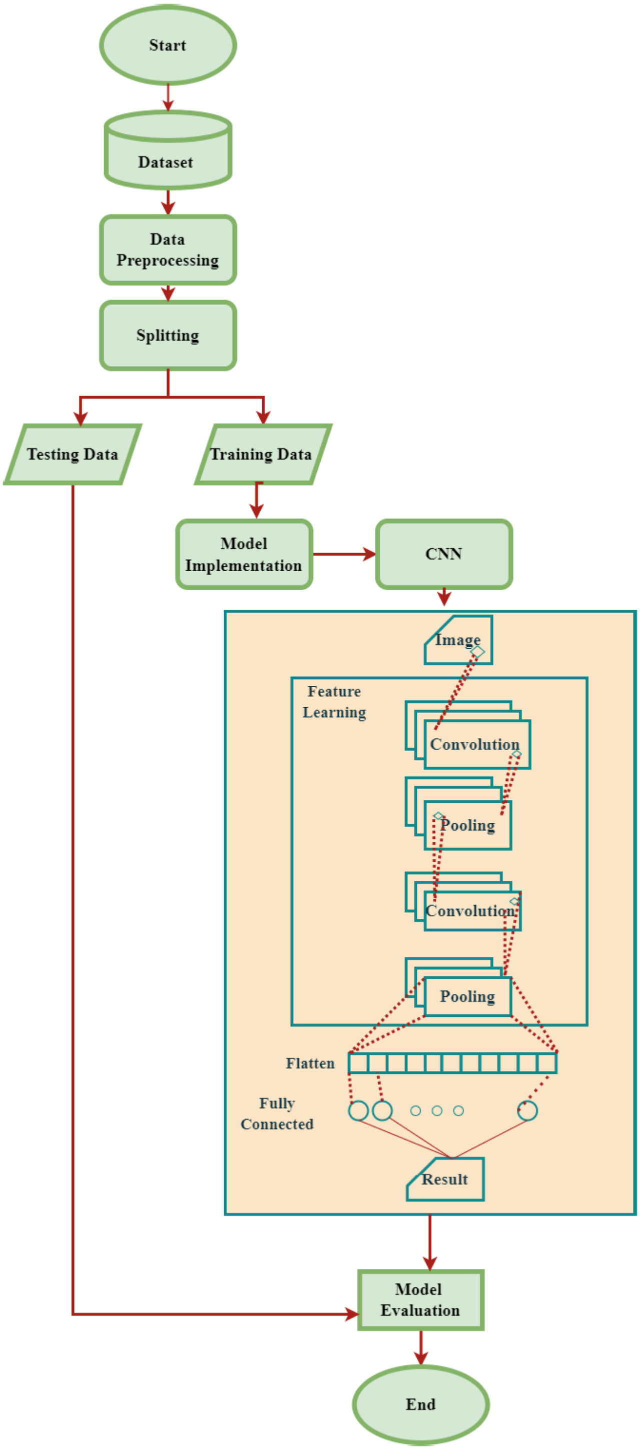

FIGURE 1. Flow chart of methodology.

2) **Image Crop:** The images were cropped to remove irrelevant parts and retain only relevant information of an image.
3) **Image Augmentation:** Image augmentation techniques were applied in rotation, flipping, zooming, and shifting to improve the model's ability in mushroom species identification. Generating additional training samples by applying random transformations to the mushroom images helped prevent model overfitting and improve the model's ability to identify mushroom species accurately.

Algorithm 1 CNN Model Training for Mushroom Image Classification

Data Collection and Preprocessing:
 Access a dataset of mushroom images: $X = \{x_1, x_2, \ldots, x_N\}$.
 Preprocess the images:
  Resize each image to 128×128: $X' = \text{resize\_to\_}128 \times 128(X)$.
  Apply image augmentation: $X' = \text{augment\_data}(X')$.
Split the Dataset:
 Dataset splitting into training $(X_{\text{train}}, Y_{\text{train}})$ and test $(X_{\text{test}}, Y_{\text{test}})$ sets.
Define the CNN Architecture:
 Define the CNN model architecture as a function $f_{\text{CNN}}(X; \Theta)$, where Θ represents the model parameters.
Compile the Model:
 Choose a suitable loss function, optimizer, and evaluation metric.
 Compile the model: $\Theta^* = \arg\min_{\Theta} \frac{1}{|X_{\text{train}}|} \sum_{i=1}^{|X_{\text{train}}|} \mathcal{L}(f_{\text{CNN}}(x_i; \Theta), y_i)$.
Train the Model:
 Model training using training data $(X_{\text{train}}, Y_{\text{train}})$.
 Update the parameters using backpropagation.
Evaluate the Model:
 Model evaluation on the test set $(X_{\text{test}}, Y_{\text{test}})$.
Fine-Tuning and Hyperparameter Tuning:
 Fine-tune the model architecture and hyperparameters.
Deployment and Monitoring:
 Deploy the trained model for inference.

The data preprocessing prepared the dataset for training the model. CNN model was trained on a dataset of mushroom images in their natural habitat. Data preprocessing and augmentation were used on the images to improve the model's performance in mushroom classification. The batches of augmented image data were supplied to the CNN model for training. During image augmentation, random transformations of the images were applied to improve the performance of the CNN model for mushroom classification. By applying transformations of mushroom images in rescaling, shearing, zooming, and horizontal flipping, the model was trained to recognize the images with different variations to accurately increase the CNN model to recognize different mushroom species. The purpose and specification of the image augmentation are given in Table. 4. The impact of preprocessing applications on mushroom images is shown in Figure.3, which shows the size of the original image and resized image along with the impact of other image augmentation applied.

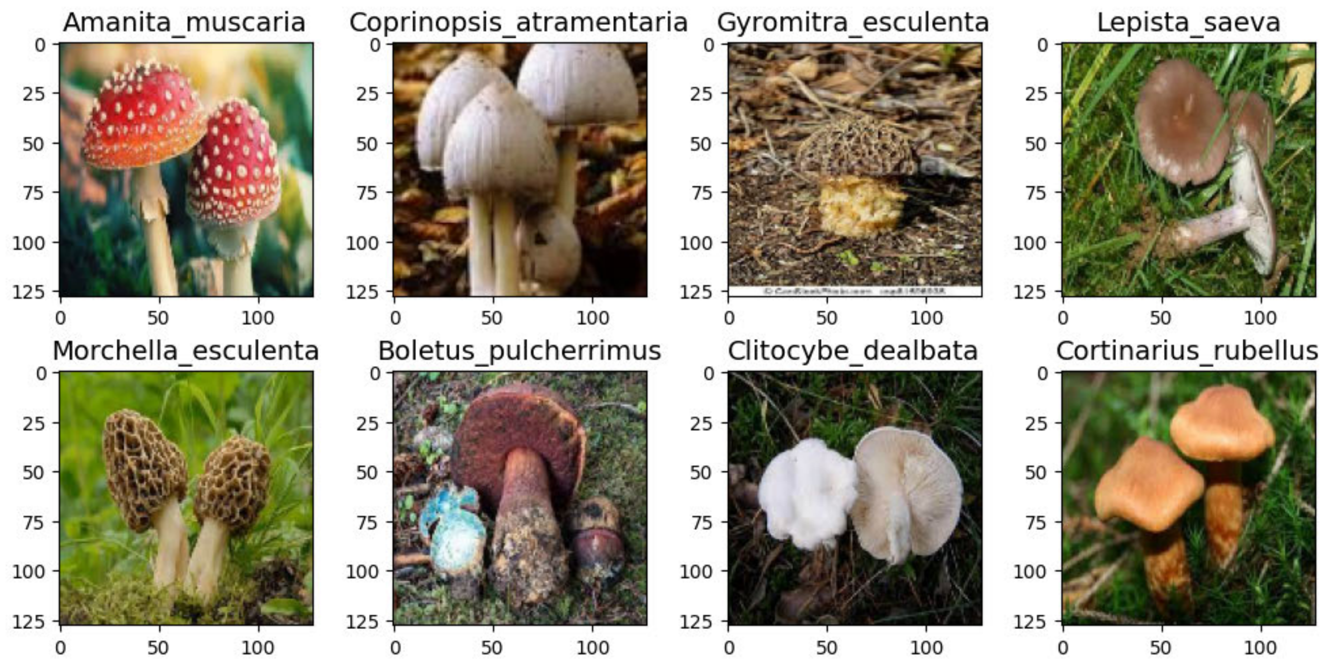

FIGURE 2. Images of mushroom species in their natural habitat.

C. DATASET SPLITTING

The dataset was split into a training and a test set into an 80:20 ratio. The 80% of the dataset was used for training purposes and 20% for validation purposes. The validation dataset is used to validate the model training. The model performance is evaluated using the unseen test dataset.

D. MODEL ARCHITECTURE

CNN is a neural network algorithm that is used in image classification. CNN model consists of multiple layers to process images and train the model. Figure. 4 shows a basic CNN model architecture combining advanced CNN layers.

The best-performing configuration of the CNN model for mushroom species classification is given in Table. 5 The CNN architecture for the study consisted of three successive convolution layers, each of which contributed to hierarchical feature extraction. In the first convolution layer, 32 filters of size sizes (3,3) were used. These filters were placed on input shape (128,128,3) with the help of the Rectified Linear Unit (*ReLU*) function. After the first convolution layer, a max-pooling layer with a pool size of (2,2) is used. The second convolutional layer comprises 64 filters of size (3,3) and *ReLU* activation function. The second convolutional layer also follows a pooling layer the same size as the first.

The third convolutional layer contained 128 filters of size (3,3) using *ReLU* activation and max-pooling with a pool size of (2,2). A flattened layer was added to convert the output to a 1D matrix of 25088 units. Two fully connected layers followed, with the first comprising 256 neurons and *ReLU* activation.

E. EVALUATION METRICS

The model was evaluated using 20% of the dataset. The effectiveness of the proposed model was assessed using accuracy, precision, recall, and Area Under the Curve (AUC) values. The evaluation metrics used for the study are defined below:

1) ACCURACY

Accuracy is used to measure the proportion of correctly identified mushroom species out of all predictions made related to mushroom species identification by the model. Accuracy was calculated using the counts of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN), as shown in Eq.1. Accuracy was observed in the range of 0 to 100 percent.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

2) PRECISION

Precision was used to quantify the accuracy of positive predictions in mushroom species classification. Precision represents the ratio of correctly identified positive instances to predicted positive instances. Precision is expressed by Eq.2.

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

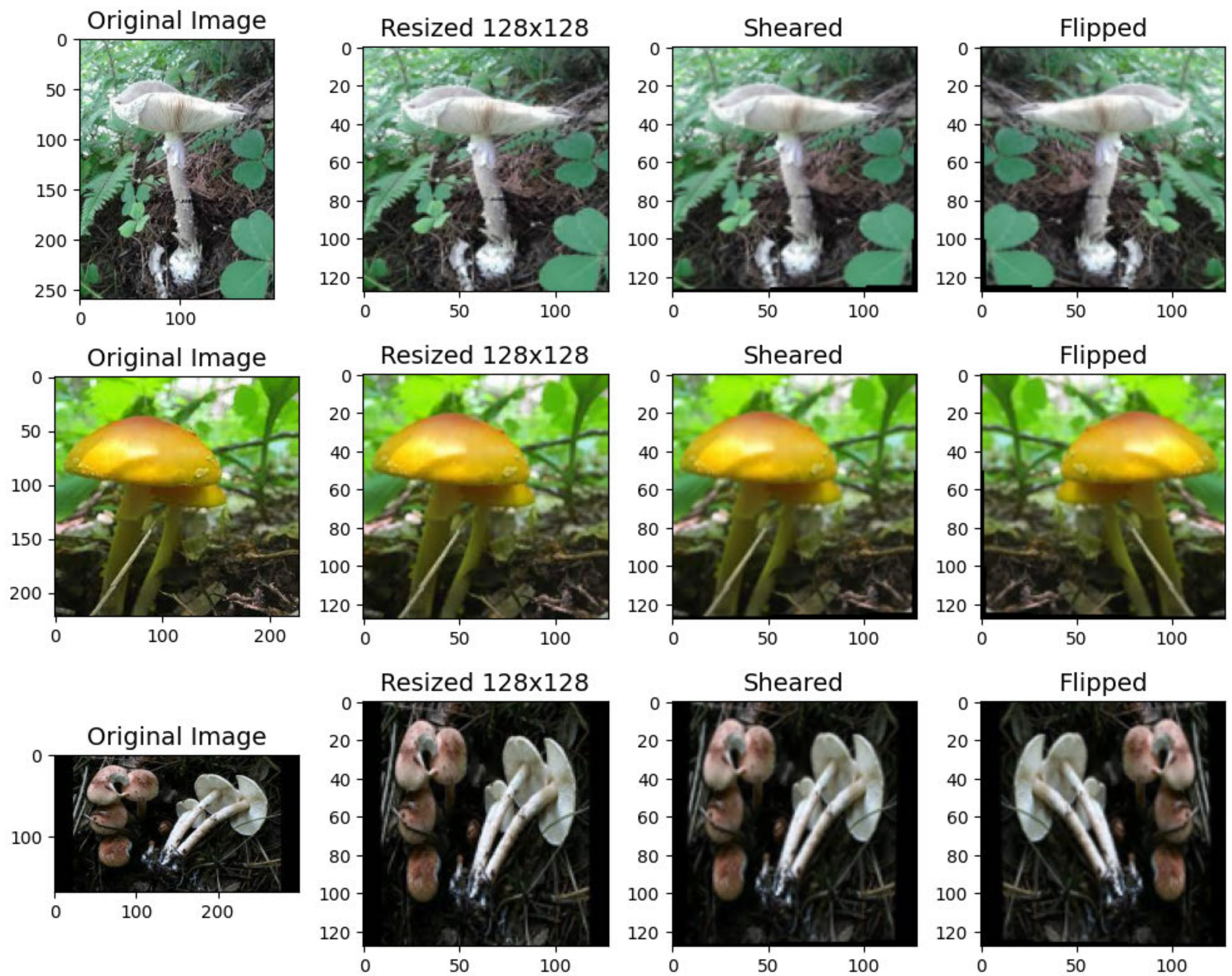

FIGURE 3. Argumentation process of mushroom images.

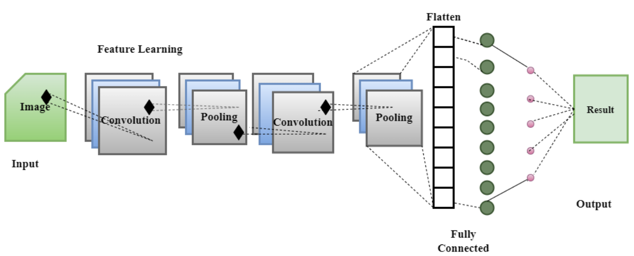

FIGURE 4. CNN architecture.

3) RECALL

Recall, or sensitivity, measures the proportion of actual positives correctly identified instances of mushroom species by the model. It is calculated using Eq.3.

$$\text{Recall}(R) = \frac{TP}{TP + FN} \tag{3}$$

4) F1 SCORE

The F1 score was used to show the balance between precision and recall for mushroom species identification. The F1 score was calculated as the harmonic mean of precision and recall defined by Eq.4.

$$\text{F1 Score} = 2 \times \frac{P \times R}{P + R} \tag{4}$$

IV. RESULTS

The model performance was evaluated using the training, validation, and test datasets. The test dataset was used to evaluate the model performance on unseen data. Figure. 5 and Figure. 6 provide an overview of the model's training process and serve as a tool to identify potential overfitting or underfitting of the model. Figure. 5 shows the accuracy results of the proposed CNN model on 103 classes of mushroom images from both the training and validation datasets. The accuracy from different datasets is given in

TABLE 3. Mushroom species distribution in the dataset.

Class	Label	Status	No of Images
Agaricus arvensis	0	E	39
Agaricus silvaticus	1	E	31
Aleuria aurantia	2	E	28
Amanita boudieri	3	P	28
Amanita caesarea	4	E	43
Amanita cokeri	5	P	20
Amanita echinocephala	6	P	32
Amanita eliae	7	P	30
Amanita flavoconia	8	P	31
Amanita flavorubescens	9	P	25
Amanita gracilior	10	P	35
Amanita hongoi	11	P	28
Amanita muscaria	12	E	51
Amanita nehuta	13	P	27
Amanita parcivolvata	14	P	28
Amanita pseudoporphyria	15	P	31
Amanita rubrovolvata	16	P	17
Amanita velatipes	17	P	29
Amanita wellsii	18	P	31
Amanita xanthocephala	19	P	19
Auricularia auricula judae	20	E	33
Boletus pulcherrimus	21	P	28
Calocera viscosa	22	P	34
Calvatia gigantea	23	E	49
Chlorophyllum brunneum	24	P	31
Chlorophyllum molybdites	25	P	38
Clavariaceae	26	E	31
Clavulinaceae	27	E	33
Clitocybe dealbata	28	P	32
Coprinellus micaceus	29	P	34
Coprinopsis alopecia	30	P	33
Coprinopsis atramentaria	31	P	57
Coprinus comatus	32	E	35
Cortinarius bolaris	33	P	34
Cortinarius callisteus	34	P	33
Cortinarius cinnabarinus	35	P	32
Cortinarius cinnamomeoluteus	36	P	56
Cortinarius limonius	37	P	54
Cortinarius rubellus	38	P	30
Cortinarius rubicundulus	39	P	49
Cortinarius smithii	40	P	49
Craterellus cornucopioides	41	E	50
Craterellus tubaeformis	42	E	54
Cudonia circinans	43	P	52
Cyclocybe aegerita	44	E	32
Entoloma albidum	45	P	32
Fistulina hepatica	46	E	30
Grifola frondosa	47	E	54
Gyromitra esculenta	48	E	44

TABLE 3. *(Continued.)* Mushroom species distribution in the dataset.

Class	Label	Status	No of Images
Gyromitra perlata	49	P	34
Hapalopilus nidulans	50	P	31
Helvella dryophila	51	P	29
Helvella lacunosa	52	P	32
Hydnum repandum	53	E	47
Hypholoma fasciculare	54	P	33
Hypholoma marginatum	55	P	32
Imperator rhodopurpureus	56	P	33
Imperator torosus	57	P	28
Inocybe hystrix	58	P	28
Inocybe lacera	59	P	33
Inocybe rimosa	60	P	31
Inosperma erubescens	61	P	30
Lactarius deterrimus	62	E	29
Leccinum scabrum	63	E	30
Leccinum versipelle	64	E	27
Lepiota castanea	65	P	30
Lepiota helveola	66	P	30
Lepiota subincarnata	67	P	34
Lepista saeva	68	E	53
Marasmius collinus	69	P	32
Morchella esculenta	70	E	58
Mycena diosma	71	P	28
Neonothopanus nambi	72	P	25
Omphalotus nidiformis	73	P	30
Omphalotus olivascens	74	P	27
Panaeolus cinctulus	75	P	47
Paralepistopsis amoenolens	76	P	31
Phallus indusiatus	77	E	54
Pholiotina rugosa	78	P	28
Podostroma cornu-damae	79	P	26
Polyporus squamosus	80	E	40
Ramaria formosa	81	P	35
Rubroboletus legaliae	82	P	32
Rubroboletus lupinus	83	P	29
Russula emetica	84	P	35
Sarcosphaera coronaria	85	P	33
Scleroderma citrinum	86	P	30
Stropharia aeruginosa	87	P	34
Stropharia rugosoannulata	88	E	32
Suillus bovinus	89	E	51
Suillus luteus	90	E	36
Suillus tomentosus	91	E	28
Tricholoma equestre	92	P	31
Tricholoma pardinum	93	P	31
Tricholoma sulphureum	94	P	20
Tricholoma terreum	95	E	29
Trogia venenata	96	P	29
Tuber borchii	97	E	28
Tuber brumale	98	E	30

TABLE 3. ***(Continued.)*** **Mushroom species distribution in the dataset.**

Class	Label	Status	No of Images
Tuber indicum	99	E	16
Tuber macrosporum	100	E	28
Tuber mesentericum	101	E	29
Turbinellus floccosus	102	P	31

TABLE 4. **Augmentation techniques used to process the images.**

Technique	Purpose	Impact	Values
Rescaling	Normalize pixel values	Efficient model training and stabilization	1./255
Shear Range	Apply shear transformations	Introduce spatial variability in training data	0.2
Zoom Range	Randomly zoom into images up to 20%	Improve robustness to scale variations	0.2
Horizontal Flip	Randomly flip images horizontally	Enhance model's ability to learn invariant features	True

TABLE 5. **Configuration of the CNN model.**

Layer (type)	Output Shape	Parameter
Convo2d_1	(None, 126, 126, 32)	896
Max_pooling_1	(None, 63, 63, 32)	0
Conv2d_2	(None, 61, 61, 64)	18496
Max_pooling2d_2	(None, 30, 30, 64)	0
Conv2d_3	(None, 28, 28, 128)	73856
Max_pooling_3	(None, 14, 14, 128)	0
Flatten	(None, 25088)	0
Dense_1	(None, 256)	6422784
Dense_2	(None, 50)	34181
Total parameters		6550215
Trainable parameters		6550213
Non-trainable parameters		0
Optimizer parameters		2

Table. 6. The analysis shows that the accuracy of classifying mushroom species is 96.10% and 96.81% from training and validation datasets, respectively. The test dataset revealed an accuracy of 96.70%. Figure. 6 shows the model loss, reflecting the error in the classification of mushroom species from both the training and validation datasets.

Table.7 gives a comprehensive classification report that shows the model's performance across one hundred and three classes of mushroom species in terms of precision, recall, F1 score and AUC values. The classification report is calculated against the test dataset. The high precision, recall, F1 score, and AUC for each mushroom species reflected the CNN model's ability to distinguish and identify each mushroom species accurately. The confusion matrix shown in Figure. 7 also provides a clear picture of the model's performance, enabling the correct identification of various mushroom species reflected in high values of true positive instances for mushroom species identification.

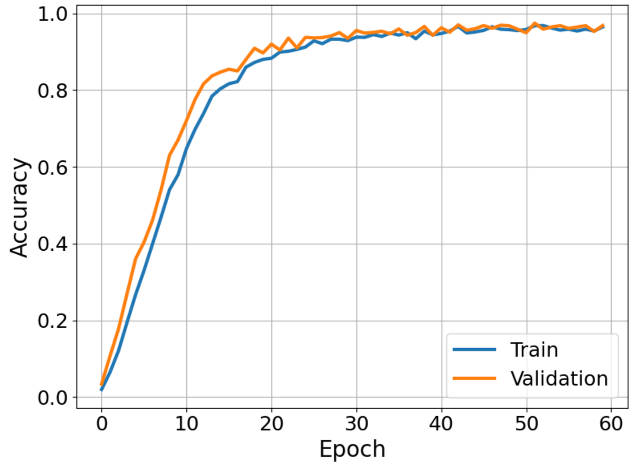

FIGURE 5. **Accuracy of the CNN model over sixty epochs.**

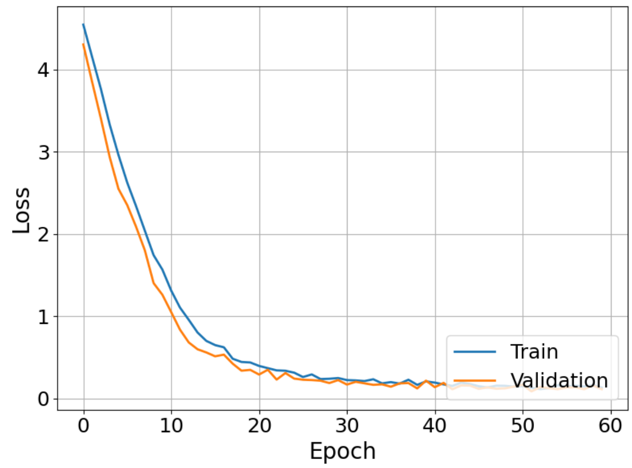

FIGURE 6. **Loss of the CNN model over sixty epochs.**

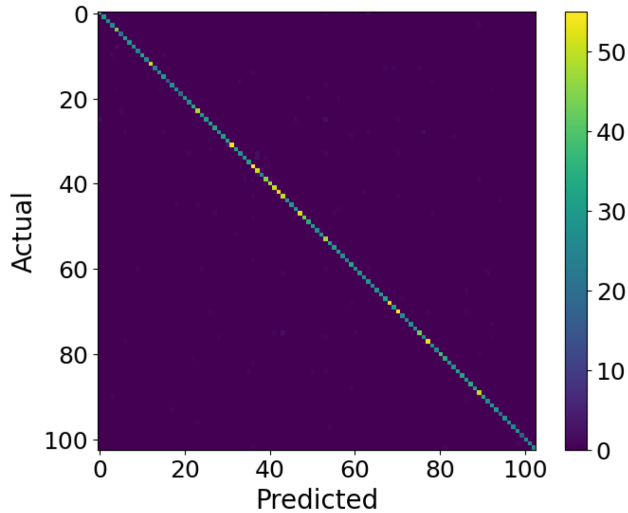

FIGURE 7. **Confusion matrix of the model.**

Table. 7 also shows the Area Under the Curve (AUC) values alongside Precision, Recall, and F1-Score metrics for each mushroom species. Figure.8 shows the ROC curves

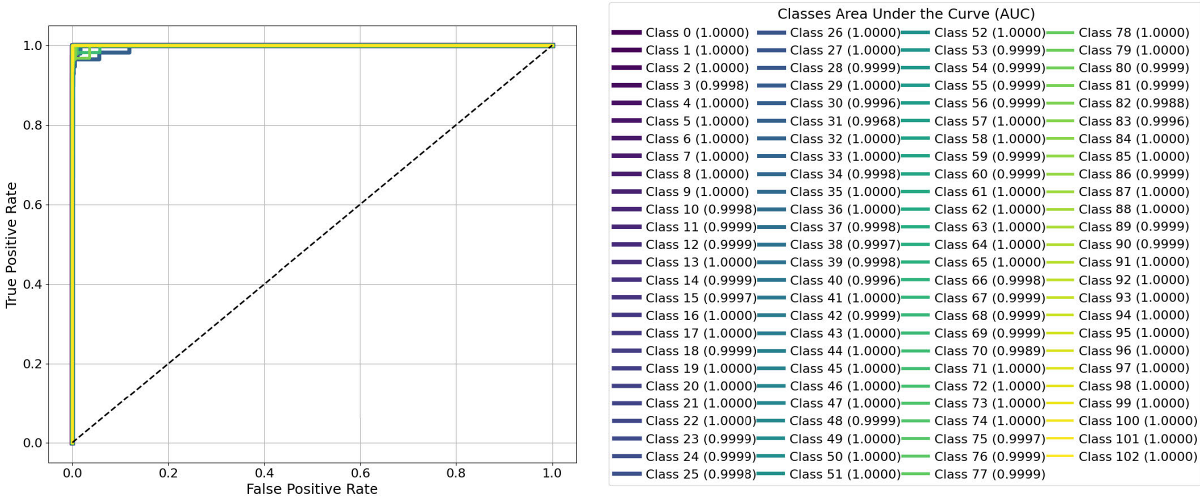

FIGURE 8. Receiver Operating Characteristics (ROC) curves and AUC values of all classes.

that represent the ability of the trained model to distinguish between different classes of mushrooms. The high values of AUC in the range of 0.99 to 1.00 for each mushroom species reflected that the model is performing well in distinguishing all the mushroom species. The high AUC values indicate that the model is very good at correctly classifying positive instances as positive and negative instances as negative.

TABLE 6. Accuracy report.

Dataset	Accuracy (%)
Training	96.10
Validation	96.81
Test	96.70

V. DISCUSSION

Accurate identification of mushroom species from their natural habitat is crucial for recognizing edible and poisonous ones. The study explored the potential of accurate identification of mushroom species using the CNN model to explore the potential of CNN model in accurate identification of mushroom species. The study's findings showed the substantial prospect of CNN for precise mushroom classification based on visual characteristics of mushroom species in their natural habitat. The model's capability to accomplish an outstanding accuracy of 96.70% emphasizes the effectiveness of CNN-based deep learning approaches in image recognition of mushroom species.

The proposed mushroom species classification model performed well with training, validation, and test datasets with 96.10%, 96.81%, and 96.70% accuracy, respectively. The accuracy of 96.70% from the unseen test dataset demonstrates that the model effectively learned to identify the various mushroom species on the unseen dataset. The high accuracy of complex mushroom images demonstrates the CNN model's ability to handle and recognize complex image patterns. The value of precision and recall in the range of 0.90 to 1.00 also suggests the model's ability to accurately recognize each of 103 classes (species) of mushrooms. The high precision and recall values indicate that the model performed well across all the mushroom species. The model's performance in accurately distinguishing different mushroom species with considerable reliability is crucial for preventing the consumption of poisonous mushrooms.

The results related to the CNN model's ability to identify the mushroom species accurately are in line with other studies [14], [25], [26], [28]. A comparison of the results of the proposed CNN model with state-of-the-art approaches is given in Table. 8. The study achieved the major contribution of one hundred and three mushroom species identification from mushroom images taken from their natural habitat. Even with a large number of mushroom species, the study achieved a 4.4% and 3.6% increase in accuracy of mushroom species identification compared to the performance of the CNN model explored by [25] and [28], respectively. The study proposed model achieved the same level of accuracy in 103 mushroom species identification compared to the accuracy achieved with 77 mushroom species in [28]. The proposed image augmentation also streamlined the objectives of accurately identifying many mushroom species from their natural habitat and playing a significant role in model performance. Preprocessing played an important role in increasing the performance of the CNN model. The augmentation technique introduced variability that helped the model learn features. The argumentation techniques help the CNN model to make accurate identifications of even images with various angles and shades.

This study has revealed the significant potential of the CNN model for accurately classifying mushroom species based on visual characteristics. The proposed solution has high accuracy in identifying mushroom classification, which reflects the ability of the CNN model to perform image

TABLE 7. Precision, Recall, F1 score, AUC score and support of all classes of mushroom species.

Label	Precision	Recall	F-1	AUC	Support
0	0.95	0.90	0.92	1.00	39
1	1.00	1.00	1.00	1.00	31
2	1.00	1.00	1.00	1.00	28
3	0.93	0.96	0.95	0.99	28
4	0.93	1.00	0.97	1.00	43
5	0.95	1.00	0.98	1.00	20
6	0.94	1.00	0.97	1.00	32
7	1.00	1.00	1.00	1.00	30
8	1.00	0.94	0.97	1.00	31
9	0.96	1.00	0.98	1.00	25
10	1.00	0.94	0.97	0.99	35
11	1.00	0.96	0.98	0.99	28
12	0.98	1.00	0.99	0.99	51
13	1.00	0.89	0.94	1.00	27
14	0.96	0.96	0.96	0.99	28
15	0.94	1.00	0.97	0.99	31
16	1.00	0.88	0.94	1.00	17
17	0.97	0.97	0.97	1.00	29
18	0.96	0.87	0.92	0.99	31
19	0.95	1.00	0.97	1.00	19
20	1.00	0.91	0.95	1.00	33
21	0.93	1.00	0.97	1.00	28
22	0.97	1.00	0.99	1.00	34
23	0.94	0.98	0.96	0.99	49
24	0.97	1.00	0.98	0.99	31
25	1.00	0.82	0.90	1.00	38
26	0.91	1.00	0.95	1.00	31
27	0.97	1.00	0.99	1.000	33
28	0.96	0.84	0.90	0.99	32
29	1.00	0.94	0.97	1.000	34
30	0.89	0.97	0.93	0.99	33
31	1.00	0.95	0.97	0.99	57
32	0.97	0.94	0.96	1.00	35
33	0.97	0.85	0.91	1.00	34
34	0.94	0.91	0.92	0.99	33
35	0.97	1.00	0.98	1.00	32
36	0.87	0.98	0.92	1.00	56
37	0.89	0.94	0.92	0.99	54
38	0.93	0.90	0.92	0.99	30
39	0.94	0.92	0.93	0.99	49
40	0.98	0.96	0.97	0.99	49
41	0.98	1.00	0.99	1.00	50
42	0.98	0.98	0.98	0.99	54
43	0.93	0.96	0.94	1.00	52
44	1.00	0.94	0.97	1.00	32
45	1.00	0.94	0.97	1.00	32
46	0.97	0.97	0.97	1.00	30
47	1.00	0.94	0.97	1.00	54
48	1.00	0.98	0.99	0.99	44
49	0.97	1.00	0.99	1.00	34
50	0.97	1.00	0.98	1.00	31

TABLE 7. *(Continued.)* Precision, Recall, F1 score, AUC score and support of all classes of mushroom species.

Label	Precision	Recall	F-1	AUC	Support
51	0.97	0.97	0.97	1.00	29
52	0.97	0.94	0.95	1.00	32
53	0.85	1.00	0.92	0.99	47
54	0.94	0.97	0.96	0.99	33
55	0.94	0.97	0.95	0.99	32
56	0.94	0.97	0.96	0.99	33
57	0.93	1.00	0.97	1.00	28
58	1.00	0.89	0.94	1.00	28
59	0.92	1.00	0.96	0.99	33
60	0.90	0.87	0.89	0.99	31
61	1.00	0.93	0.97	1.00	30
62	0.97	1.00	0.98	1.00	29
63	0.88	1.00	0.94	1.00	30
64	1.00	1.00	1.00	1.00	27
65	1.00	0.97	0.98	1.00	30
66	0.97	1.00	0.98	0.99	30
67	0.97	0.94	0.96	0.99	34
68	1.00	0.98	0.99	0.99	53
69	0.97	1.00	0.98	0.99	32
70	0.95	0.95	0.95	0.99	58
71	0.97	1.00	0.98	1.00	28
72	1.00	1.00	1.00	1.00	25
73	1.00	0.97	0.98	1.00	30
74	1.00	1.00	1.00	1.00	27
75	0.98	0.91	0.95	0.99	47
76	0.93	0.90	0.92	0.99	31
77	0.98	0.98	0.98	1.00	54
78	0.93	1.00	0.97	1.00	28
79	1.00	1.00	1.00	1.00	26
80	1.00	0.97	0.99	0.99	40
81	0.97	0.97	0.97	0.99	35
82	0.97	0.94	0.95	0.99	32
83	0.93	0.97	0.95	0.99	29
84	1.00	0.91	0.96	1.00	35
85	1.00	1.00	1.00	1.00	33
86	0.91	1.00	0.95	0.99	30
87	1.00	1.00	1.00	1.00	34
88	1.00	0.97	0.98	1.00	32
89	0.93	0.98	0.95	0.99	51
90	0.97	0.94	0.96	0.999	36
91	0.96	0.96	0.96	1.00	28
92	0.91	0.97	0.94	1.00	31
93	1.00	0.97	0.98	1.00	31
94	0.91	1.00	0.95	1.00	20
95	1.00	1.00	1.00	1.00	29
96	1.00	0.97	0.98	1.00	29
97	1.00	0.93	0.96	1.00	28
98	0.94	1.00	0.97	1.00	30
99	0.94	1.00	0.97	1.00	16
100	1.00	1.00	1.00	1.00	28
101	1.00	0.93	0.96	1.00	29
102	1.00	0.94	0.97	1.00	31

TABLE 8. Study results comparison.

Study	Accuracy	Mushroom Species	Comparison
[25]	93.1%	27	3.6% increase with 103 mushroom species
[39]	92.6%	106	4.4% increase in accuracy
[28]	97%	77	Nearly similar accuracy of 96.70% with 103 Mushroom species

classification with many classes and complex images. The performance of the CNN model for mushroom image classification opened the way for CNN applications in other real-world applications. The proposed solution has several implications for stakeholders, such as scientists, researchers, mycologists, and food specialists. The foremost importance of the proposed solution is the safe usage of mushrooms for food. The proposed solution has important implications for preventing the consumption of poisonous mushroom species and promoting informed decision-making regarding edible mushroom selection.

Mushroom species identification has an important role in their safe usage, especially the application of mushrooms for food purposes. The accurate identification of mushroom species not only helps to prevent the usage of poisonous mushrooms for food purposes but also serves as an important tool for ecologists to identify the mushroom species accurately. The proposed solution can serve as a valuable tool for recognizing mushrooms in a particular area for biodiversity and ecological monitoring of mushroom growth in a particular area. The proposed solution is important in understanding the fungal biodiversity in ecology monitoring.

Future research could further explore the integration of additional features such as texture analysis, environmental factors, and genetic information to enhance the accuracy and reliability of mushroom classification models. Expanding the dataset to include a broader range of mushroom species and incorporating advanced techniques such as transfer learning and ensemble methods could yield even more robust and versatile models. While the study focuses on automated detection, future research could involve agricultural validation studies to assess the real-world applicability and accuracy of the proposed model.

VI. CONCLUSION

The CNN-based approach was proposed to classify large mushroom species effectively. The experimental results demonstrate the remarkable ability of the CNN model to distinguish and classify many mushroom species accurately. It is worth noting that this model achieves high accuracy and an impressive success rate of 96.70% in mushroom classification. The high precision, recall, F1 score and Area Under the Curve (AUC) values for each of the mushroom species also revealed the high capability of the proposed CNN model to classify each mushroom species accurately. The performance of the CNN model highlights the CNN model practicality, efficiency, and promising contribution to the accurate classification of mushroom species identification. The proposed solution has several practical implications for the safe and accurate usage of mushroom species. The application of advanced image processing, deep learning approaches, and data enhancements with more mushroom species is recommended for future work.

DATA AND CODE AVAILABILITY

Code and data can be accessed from here;

1) Code
2) Dataset

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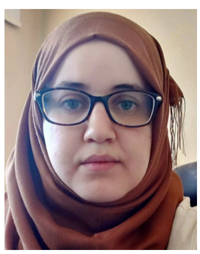

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