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Review

Intelligent Mushroom Classification with Machine Learning and Deep Learning: A Comprehensive Survey and Future Directions

Aythem Khairi KAREEM[1,*], Ahmed Adil NAFEA[2], Sameeh Abdulghafour JASSIM[3], Afrig AMINUDDIN[4], Nor Samsiah SANI[5], Manar AL-MAHDAWI[6], Mustafa Nadhim OWAID[1,7]

[1] *Department of Heet Education, General Directorate of Education in Anbar, Ministry of Education, Heet, 31007 Anbar, Iraq*
[2] *Department of Artificial Intelligence, College of Computer Science and IT, University of Anbar, Ramadi, Iraq*
[3] *Department of Computer Sciences, College of Science, University of Al Maarif, Al Anbar,31001, Iraq*
[4] *Faculty of Computer Science, Universitas Amikom Yogyakarta, Sleman, 55283, Indonesia*
[5] *Center for Artificial Intelligence Technology, Faculty of Information Science & Technology, Universiti Kebangsaan Malaysia, Bangi, Selangor, Malaysia*
[6] *Department of Scientific Affairs and Graduate Studies, College of Science, AL-Nahrain University, Jadriya, Baghdad, 10072, Iraq*
[7] *Department of Environment, College of Applied Science-Heet, University Of Anbar, Heet, 31007 Anbar, Iraq*

* Corresponding author: ayt19c1004@uoanbar.edu.iq

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ABSTRACT: Mushroom classification is of significant importance in agriculture, ecology, and food safety; however, accurate classification is non-trivial, as mushrooms exhibit considerable morphological variation, high inter-class similarity, and a shortage of large-scale annotated data. Recent developments in Artificial Intelligence (AI), specifically in Machine Learning (ML) and Deep Learning (DL), have brought powerful remedies to these concerns. This study provides a comprehensive overview of ML and DL techniques in the context of mushroom classification and edibility prediction. We compare trained classical ML techniques and models, such as decision trees, random forests, support vector machines, and ensemble models, to modern DL architectures (e.g., CNNs, transfer learning models, and lightweight network design optimal for mobile) in the context of these objectives. The survey also reviews hybrid approaches, object detection models, and data balancing methods, and presents how they affect classification performance. Cross-dataset comparison suggests that, under controlled conditions, ML and DL can achieve nearly perfect accuracy, while challenges such as generalization, small datasets, and class imbalance are observed. We conclude the paper by discussing critical challenges, such as large-scale curated datasets and resistance to environmental variations, and then present the future directions of this burgeoning field, including multimodal fusion, real-time mobile applications, and domain adaptation techniques. This survey serves as a quick reference for researchers and practitioners who aim to develop intelligent mushroom recognition systems.

Keywords: Deep Learning, Food Safety, Machine Learning, Mushroom Classification, Mycology.

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1. INTRODUCTION

In last years, the mushroom field was an important industry especially in agricultural biotechnology owing to the ecological, nutritional, and pharmacological importance of macrofungi (Owaid, 2020; Owaid, Abed, et al., 2017;

Pérez-Moreno et al., 2021). Edible macrofungi are among the best functional food groups with a wide range of nutritional and medical applications due to their proteins, essential amino acids, dietary fibers, and a variety of bioactive compounds (Owaid et al., 2015; Owaid, et al., 2017) with antioxidant (Debnath et al., 2013) and immunomodulatory properties (Alaubydi & Abed, 2011; Chan et al., 2008). Apart from their nutraceutical significance, mushrooms play crucial ecological roles through their ability to transform agricultural waste into nutritious food products (Owaid et al., 2018), which benefits the circular bioeconomy (Pathak et al., 2022). One of the major challenges faced by farmers and people working on farms is the inability to distinguish between edible and poisonous types of mushrooms. Therefore, this issue represents a significant problem that requires a solution through the use of artificial intelligence techniques to easily differentiate between these types (Bakaitis, 2025).

Recently, with the advancement of AI techniques, especially ML and DL, these techniques have become essential and practical tools in mushroom classification. ML techniques can handle multi-dimensional and multivariate data and discover hidden associations within data in complex and dynamic conditions. The relevance of different ML techniques varies significantly across various problems, fields, and dataset types (Nabavi-Pelesaraei et al., 2023). ML techniques have proven their competency in learning, acquiring, and mastering complicated tasks. They have also revealed the ability to observe patterns that are beyond manual discernment. This novelty has significantly enhanced the importance of applying ML techniques to mushroom classification. ML techniques are classified into supervised and unsupervised learning. There are several types of ML techniques, including Support Vector Machine (SVM), Bagging, DT, Quadratic Discriminant Analysis (QDA), K-Nearest Neighbors (KNN), Logistic Regression (LR), Adaptive Boosting (Adaboost), Naïve Bayes (NB), Gradient Boosting (GB), and RF. Each technique differs from the others in terms of its underlying framework, including the learning paradigm and algorithmic design, as well as in its performance, which encompasses accuracy, scalability, interpretability, and suitability for various types of data and tasks (Agarwal et al., 2021; Nafea et al., 2024; Neeraj & Maurya, 2020). DL is part of the ML concept, automating learning by mimicking the human brain's operation. It employs the performance of multiple layers of neural networks, enabling complex processing and achieving high accuracy. Additionally, DL techniques are more accurate than traditional ML classifiers due to the large datasets that train them. Therefore, DL is widely used in mushroom classification. DL consists of three layers: the input layer, the hidden layer, and the output layer. There are several types of DL techniques, including Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN) (Ketwongsa et al., 2022). The CNN is a multiple-layer neural network model, which is a popular DL technique that is employed for image analysis. It includes several types, such as VGG16, AlexNet, ResNet-50, GoogLeNet, EfficientNet, MobileNet, and ConvNeXt, each technique differing in terms of architecture design, efficiency, depth, and application focus, varying from large-scale image classification to lightweight mobile deployment and modern transformer-inspired models (Zhu et al., 2023). On the other hand, You Only Look Once (YOLO) is a DL technique that is used for object detection, classification, and recognition in computer vision tasks. It is employed to locate and identify objects within videos or images. The main architecture of YOLO comprises a head network, a neck network, and a backbone network, featuring specific components such as focal loss, multi-scale prediction, and anchor boxes, and which collectively improve the model's performance (Aghajani et al., 2024; Qi et al., 2025; Kareem et al., 2025).

The main objective of this review can be summarized as follows: (1) Present a comprehensive synthesis of ML and DL techniques applied to mushroom classification and edibility prediction. (2) Evaluate and compare the performance of traditional ML algorithms, modern DL architectures, and hybrid approaches. (3) Analyze the impact of datasets, preprocessing, and data balancing strategies on classification outcomes. (4) Identify key challenges such as dataset limitations, class imbalance, and generalization issues. (5) Highlight future research directions for developing robust, real-time, and practical mushroom recognition systems.

The remainder of this paper is organized as follows: Section 2 discusses some shapes of mushrooms. Section 3 discusses classical ML techniques for mushroom classification. Section 4 explores DL architectures, including CNNs, transfer learning, and YOLO. Section 5 presents a comparative analysis of existing studies. Section 6 discusses challenges and future research directions, while Section 7 concludes the paper.

2. BACKGROUND AND TAXONOMY OF MUSHROOMS

The scientific study of fungi, known as mycology, has evolved significantly since its early classification under the plant kingdom by Carl Linnaeus in the 18th century, using the system of binomial nomenclature. Early observations focused primarily on macroscopic features of mushrooms, but advances in microscopy during the 19th century enabled deeper insights into fungal structures and reproduction. The 20th century marked a turning point with the development of molecular biology techniques, which revolutionized fungal taxonomy and phylogeny (Reid, 2009). Today, mycology integrates morphological, biochemical, and genomic data to provide a comprehensive understanding of fungal diversity and evolution (Takashima et al., 2026).

2.1. Key Biological Features of Mushrooms

Mushrooms are the reproductive fruiting bodies of certain fungi, primarily belonging to the phylum Basidiomycota. They are characterized by a mycelial network composed of hyphae, which absorb nutrients from organic matter (Chang & Miles, 2004). Key biological features include spore production, heterotrophic nutrition, and symbiotic or saprophytic lifestyles. Mushrooms play essential ecological roles such as decomposition, nutrient cycling, and symbiosis with plants (mycorrhizae). Their structural diversity and biochemical complexity also make them valuable for food, medicine, and biotechnology applications (Dias & de Brito, 2017).

Morphological characteristics are fundamental in traditional mushroom identification. Features such as cap shape, gill color, spore print, stipe (stem) structure, and surface texture provide critical diagnostic information. Despite advances in molecular techniques, these visual traits remain essential for field identification and are often the first step in classification. However, morphological similarity between toxic and edible species can lead to misidentification, highlighting the need for more precise tools (Tsujikawa et al., 2003).

2.2. Taxonomic Classification

Fungal taxonomy follows a hierarchical classification system: Kingdom, Phylum, Class, Order, Family, Genus, and Species. Mushrooms are classified under Kingdom of Fungi, with most edible and toxic species belonging to Basidiomycota and Ascomycota (Chang & Miles, 2004). Traditional classification relied on morphological characteristics such as spore-bearing structures, but modern taxonomy increasingly depends on molecular phylogenetics (Du et al., 2012), including DNA sequencing of ribosomal RNA genes. This integrated approach improves accuracy in identifying closely related species and understanding evolutionary relationships.

2.3. Distinction Between Edible, Medicinal, and Poisonous Mushrooms

Mushrooms can be broadly categorized into edible, medicinal, and poisonous types based on their biochemical composition and physiological effects. Edible mushrooms provide essential nutrients (Meghwal & Goswami, 2012) such as proteins, vitamins, and antioxidants, while medicinal mushrooms possess bioactive compounds with immunomodulatory (Devi et al., 2013) and anticancer properties (Kim et al., 2009). In contrast, poisonous mushrooms contain toxic compounds such as muscarine, which can cause severe organ damage or death (Noll & Ew, 2012). Accurate identification is therefore critical to prevent poisoning incidents and to utilize beneficial species effectively. Some shapes of mushrooms are presented in Figure 1.

2.3.1. Agaricus

The genus *Agaricus* includes widely consumed edible species such as *Agaricus bisporus*. It is commonly studied due to its economic importance and morphological variability (Cunha et al., 2013; Owaid, 2015; Owaid et al., 2017).

2.3.2. Amanita

The genus *Amanita* contains some of the most dangerous mushrooms, including *Amanita phalloides* (death cap), responsible for the majority of fatal mushroom poisonings worldwide (Satora et al., 2006; St et al., 2012).

2.3.3. Pleurotus

The genus *Pleurotus*, commonly known as oyster mushrooms, is widely cultivated and valued for its nutritional and medicinal properties (Bermúdez et al., 2001; Mikiashvili et al., 2006; Owaid et al., 2017).

These genera are frequently used in classification and machine learning datasets due to their diversity and clear morphological differences. Morphological features serve as key input variables in machine learning models for mushroom classification. Attributes such as cap color, odor, gill spacing, and spore characteristics can be encoded into structured datasets for supervised learning algorithms. Techniques such as decision trees, support vector machines, and neural networks have been successfully applied to distinguish between edible and poisonous mushrooms with high accuracy. Integrating image-based features and deep learning further enhances classification performance, offering a practical solution for real-world identification challenges (Jacob et al., 2025).

Figure 1. Some macrofungal fruiting bodies

3. ML TECHNIQUES FOR MUSHROOM CLASSIFICATION

This section describes the machine-learning methods used to categorize species of mushrooms. The investigation includes a series of algorithms that identify the most effective method for differentiating among mushroom species. We begin with a data collection and data preprocessing steps, respectively. After that, we will explain the model selection of a study of the fundamental models of traditional ML algorithms, including DT, RF, SVM, K-Nearest Neighbors, and LR. Later, we assess the efficacy of advanced ensemble methods like AdaBoost, XGBoost, and Bagging, which combine multiple models to improve performance and have a greater degree of robustness. Ultimately, we explore the potential of DL frameworks, specifically ANN, CNN, You Only Look Once (YOLO), and Transfer Learning, for increasing the effectiveness of this task on images. The structures of this section are illustrated in Figure 2.

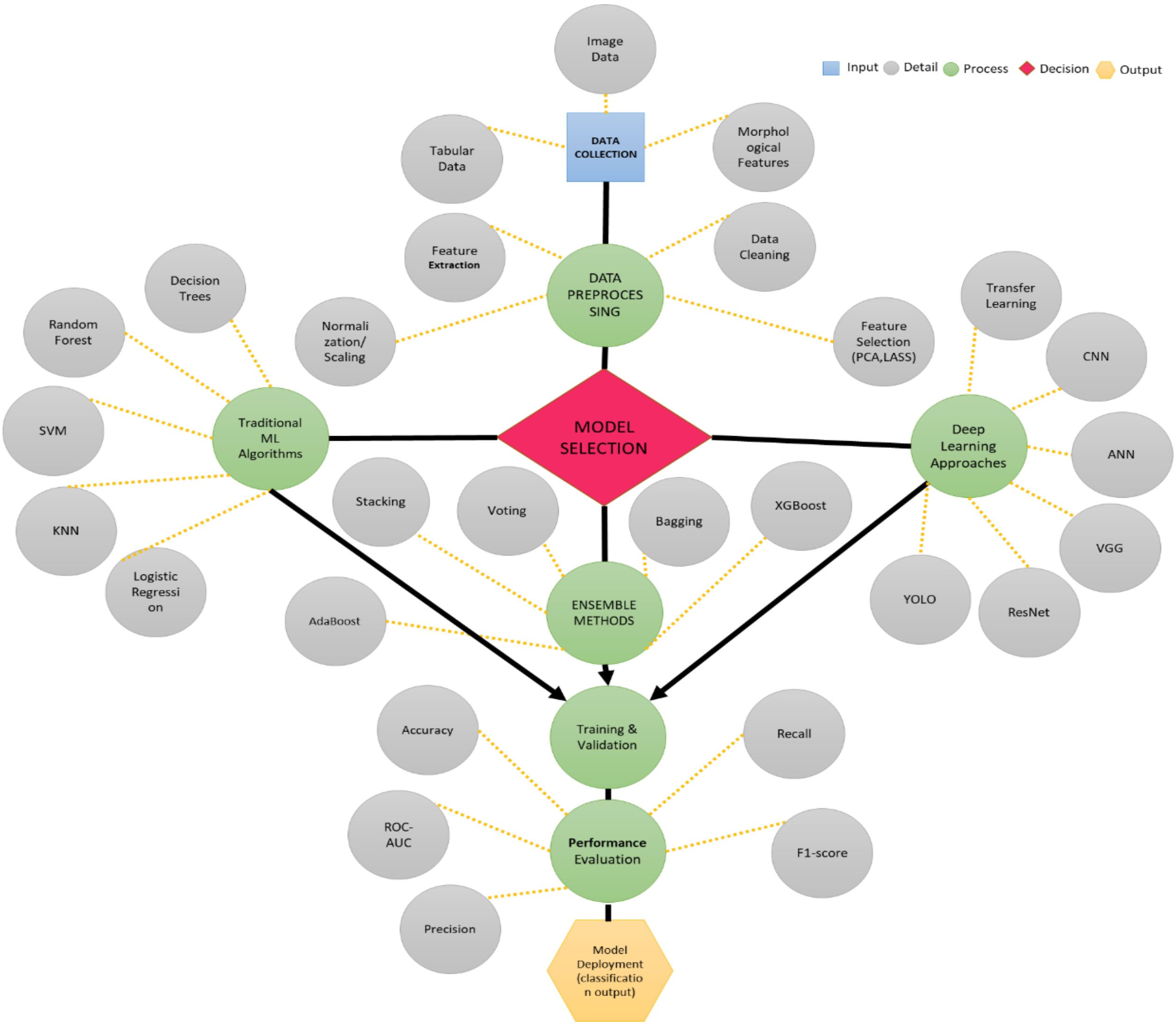

Figure 2. ML Workflow for Mushroom Classification

3.1 Data Collection

The performance of ML and DL models for the smart classification of mushrooms relies primarily on the quality, variety, and amount of training data. Latest advances within the same enable a transition from the traditional usage of simple image sets to a multimodal paradigm that combines visual, tabular, and morphologically extracted features. The paradigm combines different data modalities such as image data taken from high-quality photographs (Ozsari et al., 2024), tabular data that include non-visual information like environmental sensor observations (Duman et al., 2024), and the computer-aided extraction of morphological features like shape and color (Neogi, 2025).

3.2 Data Preprocessing

Data preprocessing is one of the fundamental and key steps of the ML pipeline and has a great impact on the effectiveness and generalizability of the output model. In the problem of mushroom classification, the raw data (often comprising images alongside tabular morph features (like cap shape, gill size, odor, etc.)) is typically plagued by incompleteness, inconsistency, and scale differences. The following steps outline the significant operations undertaken to refine such unprocessed data into a refined, orderly dataset worthy of training competent ML and DL models:

1. Feature Extraction: The Feature extraction in ML plays a crucial role in converting raw images into meaningful numerical descriptors (texture, shape) and interpretable representations (Dehbozorgi et al., 2025; Abd Al-Rahman & Jassim, 2024).
2. Normalization/Scaling: Scaling numerical columns into the same scale for fair comparability by the model (Admojo et al., 2024).
3. Data Cleaning: Error, inconsistency, and missing value identification and fixing at the dataset level (Sulistianingsih & Martono, 2025).
4. Features Selection: Utilizing such algorithms like Principal Component Analysis (PCA), and LASSO for the selection and maintenance of only the important features, improving the efficiency and performance of the model (Ortiz-Letechipia et al., 2024).

3.3 Model Selection

This section starts with an examination of the fundamental Traditional ML Algorithms, proceeds through higher-level Ensemble Methods that aggregate multiple models for the purposes of stronger prediction, and finishes with the utilization of DL architectures specifically crafted for working with the complexities associated with image data.

3.3.1 Traditional ML Algorithms

This part of the study evaluates the fundamental capabilities of traditional ML algorithms in the classification of mushrooms, and it establishes the basic performance metrics for DT, RF, SVM, KNN, and LR.

3.3.1.1 Decision Trees

DT are represented by a tree-like configuration that branches the dataset into different groups of data based on the value of a particular attribute at each node. For mushroom classification, trees learn rules such as (odor = foul ➔ poisonous) and (gill-size = broad ➔ edible). DT are valued for simplicity, transparency, and quick inference, but can overfit noisy data if not pruned (Maurya & Singh, 2019; Jabbari et al., 2012).

Recent studies of mushrooms have demonstrated impressive accuracy with DT on datasets based on features, and tree visualization is common in these investigations (Wibowo et al., 2018).

3.3.1.2 Random Forest

The RF incorporates multiple trees of decision making with bootstrapped data and random feature selection in order to reduce overfitting and increase accuracy. Every tree has a vote, and the majority of the class is elected. RF have become the most accurate of the mushroom tabular methods; they have a tendency to achieve a near-perfect (almost 100%) accuracy, this is especially true when the features are selected and encased appropriately (Paudel & Bhatta, 2022; Wagner et al., 2021).

3.3.1.3 Support Vector Machine (SVM):

SVM finds the optimal hyperplane that differentiates between edible and poisonous classes by maximizing the distance between support vectors. With kernel functions, SVM is capable of dealing with relationships that are not linear (e.g., species that have a single feature that cannot differentiate between classes easily). Studies of mushrooms have demonstrated that the SVM's accuracy and recall are comparable to, or superior to, other ML methods when features are designed with a specific purpose in mind. SVM is a common base in the modern literature on comparison machines (Masoudian & Mcisaac, 2013; Jassam et al., 2025).

3.3.1.4 K-Nearest Neighbors (KNN):

The K-NN algorithm is an algorithm of the form, where it estimates the output class of the test data by measuring the distance of the test data from all the training points. Figure 3 shows an example of K-NN algorithm before and after points classification (Kufel et al., 2023).

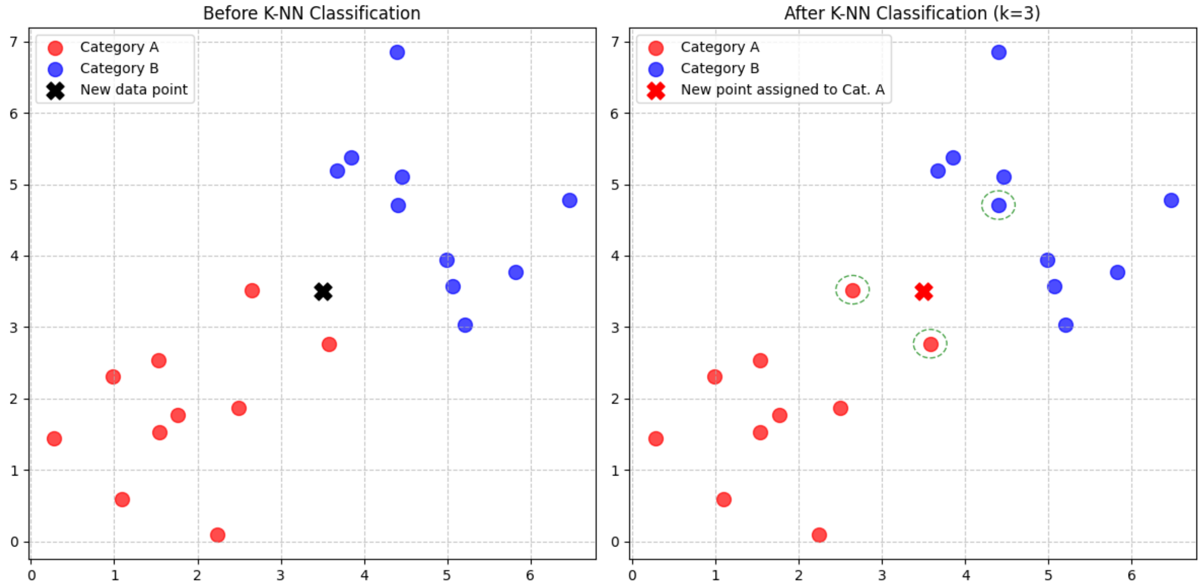

Figure 3. An example of K-NN algorithm before and after classification

KNN classifies an instance by the majority class among its k closest neighbors in the feature space. Particularly beneficial to datasets with mushrooms, because of their natural cluster composition, KNN models are simple to visualize (by drawing out the feature clusters and their neighbors) and have a tendency to deliver 98-100% accuracy in the attribute-based task of mushroom identification (Wibowo et al., 2018).

3.3.1.5 Logistic Regression:

LR estimates the probability of an object being of one of two classes. It employs a logistic function to convert predicted values from 0 to 1. This algorithm determines the connection between the input variables and the target variable. LR assists in answering the inquiries regarding the probability of events or membership in a group based on the properties of the data, such as shape and the categorization of mushrooms (Kufel et al., 2023).

LR models the probability of a sample being categorized as a species of mushroom as a logistic (sigmoid) function of its features. It's simple to understand and beneficial as a starting point; studies have demonstrated that it has a strong degree of accuracy when the true boundaries of classes are near the linear boundary.

3.3.2 Ensemble Methods

This subsection discusses ensemble methods, which utilize multiple individual classifiers to increase the accuracy and stability of predictions greater than the individual classifiers. Specifically, we investigate the methods of AdaBoost, XGBoost, and Bagging.

3.3.2.1 AdaBoost:

Adaboost, abbreviated as adaptive boosting, is a machine-learning algorithm that is used to classify and predict things in binary form. It's a relatively recent ML algorithm that is non-linear (Kufel et al., 2023). Adaboost is a method of increasing the weight of misclassified instances that trains multiple weak models on different parts of the training data and increases the weight of the instances that are misclassified in each iteration. In subsequent steps, the algorithm prioritized the misclassified samples, which led to the weak models having the opportunity to learn from their errors and improve on their effectiveness, following which they are combined to form a single strong classifier (Li et al., 2020).

3.3.2.2 XGBoost:

XGBoost, which is dedicated to enhancing the gradient of learning, is a popular ML algorithm that has been successful in multiple domains, including the classification of mushroom species. It's a hybrid learning method that combines the predictions of several individually trained weak trees of decision making to produce a more accurate and more powerful model (Kufel et al., 2023).

Moreover, XGBoost is a common variant of Gradient Boosting that is regularized. It is popular for its superior performance in predictions. In recent years, the performance of XGBoost has been superior to other competitors in mushroom identification. It is particularly strong on datasets with high dimensions or noise, and it is commonly compared to the RF in modern research. The XGBoost workflows prioritize the validation of predictions, the tuning of parameters, and the importance of features (Chen, 2025).

3.3.2.3 Bootstrap Aggregating (Bagging):

Bagging is one of the simplest and most natural methods of ensemble. The fundamental idea is to reduce the variation of a model by creating multiple different datasets that are prepared through bootstrapping (testing with substitutions). For each Bootstrapped experiment, a different model (normally a DT) is created, and the expectations of all models are found at the middle of the range for recurring activities or the majority of the activity is devoted to the classification task. Through the training of each tree on different parts of the information, Bagging averts the overfitting that often occurs when base learners are susceptible to it (for example, DT), and decreases the probability of it, specifically when the base learners are already at a high degree of change (Arslan et al., 2024).

3.3.3 Deep Learning (for Image Data)

This subsection explores advanced DL architectures designed for image recognition tasks. The methodologies covered are ANN, CNN, Transfer Learning with pre-trained networks, and You Only Look Once (YOLO).

3.3.3.1 Artificial Neural Networks (ANNs)

ANN are computational models that are inspired by biological neural systems; they deduce hierarchal relationships from inputs (e.g., mushroom images or tabular attributes) to outputs (species or edibility labels) by altering the weights of connections in order to optimize them. ANNs range from simple multilayer perceptrons (MLPs) to deep convolutional or attention-based networks. Modern surveys summarize the advances in design, training regimes, and practical considerations (regularization, pruning, and compression) that directly affect the performance of fine-grained visual tasks like the classification of mushrooms (Mienye & Swart, 2024).

ANNs typically have multiple layers: an input layer that receives the features, one or more hidden layers that neurons in these layers process the input through weighted connections and non-linear activation functions, and an output layer that produces the classification information. The neurons in each layer add their inputs with the weight of their connection, add a bias, and then utilize an activation function (such as ReLU, sigmoid, or tanh) that is not linear to introduce nonlinearity. This enables the network to learn complex boundaries for decision making (Kufel et al., 2023).

The key steps involved in applying ANNs to mushroom classification include (Mienye & Swart, 2024):

1. Data Preprocessing: A raw mushroom dataset (e.g., raw physical qualities or image pixels) is normalized or encoded for preparation for input into the network.
2. Network Initialization: The ANN architecture is defined, involving the number of layers, neurons per layer, activation functions, and weights, often initialized randomly.

3. Forward Propagation: Input features traverse through the network layers, where each neuron's weighted activation is computed, culminating in an output prediction.
4. Loss Computation: Predicted output is compared with the true label via a loss function (like cross-entropy for classification), whose objective is error measurement of the prediction.
5. Backpropagation and Weight Update: Loss gradients with respect to network parameters are estimated through backpropagation, and the weights are updated by the optimization algorithms such as Adam or the stochastic gradient descent for error minimization.
6. Evaluation of Model: The developed model is evaluated on unseen data by measuring performance metrics like accuracy, precision, recall, and F1-score to check for the generalization ability of the model.

3.3.3.2 Convolutional Neural Networks (CNNs)

CNNs are superior to other computers for automatically extracting features from images. With layers of convolution, pooling, and non-linear activation, CNNs have the ability to efficiently learn the unique patterns, shapes, and coloring of each species of mushroom. Frequently, published articles discuss the comparison of standard CNNs with more advanced networks (Mansourvar et al., 2024; Wang, 2022).

Works such as Ketwongsa (2022) compare architectures (ResNet-50, GoogLeNet, custom CNNs) on mushroom morphology, consistently achieving 91-99% accuracy (Ketwongsa, 2022).

Moreover, CNNs are the state of the art for image-based mushroom classification; their design is specifically geared towards recognizing mushrooms and achieving exceptional accuracy (Bashir et al., 2024), as shown in Figure 4.

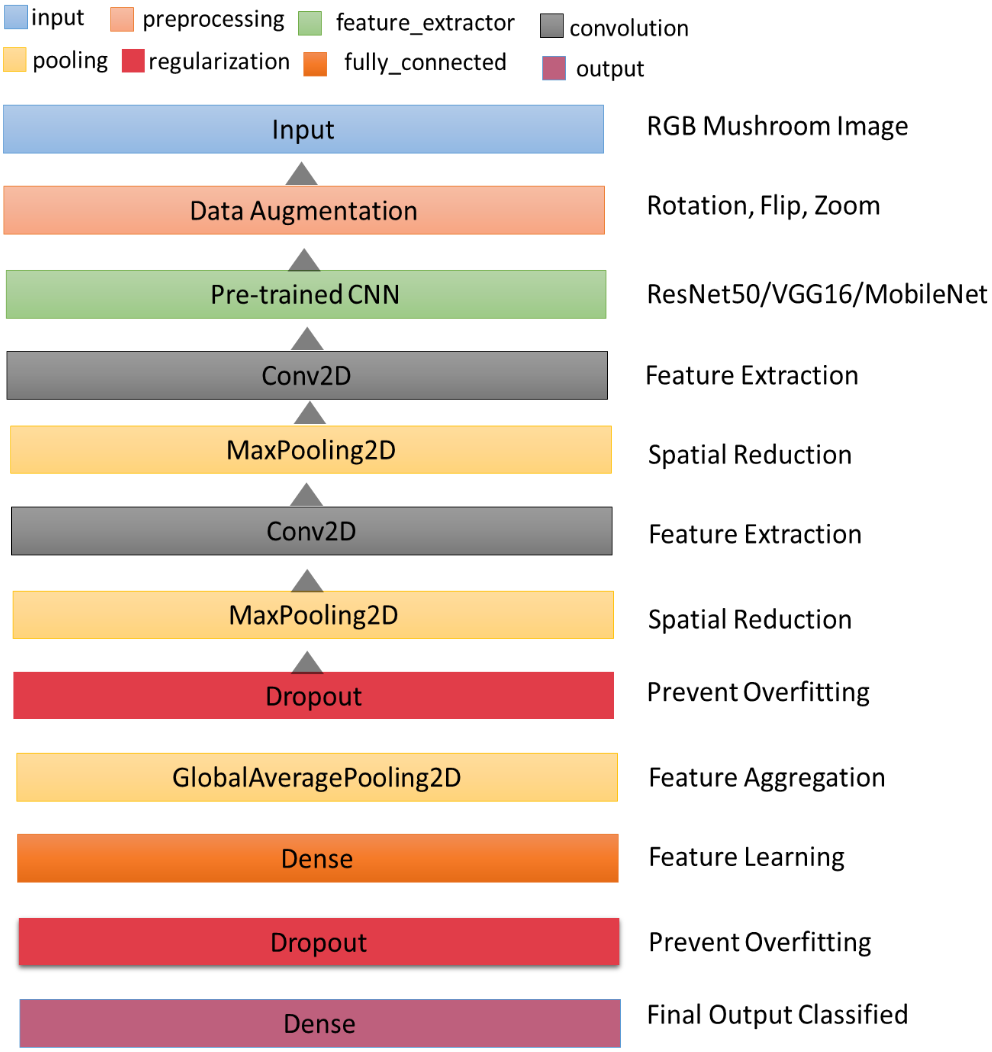

Figure 4. DL (CNN-based) Workflow for Mushroom Classification

2.3.3.3 Transfer Learning (ResNet, VGG):

Transfer learning capitalizes on pretrained CNNs (e.g., ResNet-50, VGG-16) that were trained on large datasets (like ImageNet) and then fine-tuned for mushroom images. The method promotes fast training and increases the accuracy of short datasets. Research has found that ResNet and VGG are among the top performers in challenging images with multiple species. Several studies have included diagrams of network blocks and feature maps (KETWONGSA, 2022). Also, vision transformers are becoming an innovative method of transferring knowledge to recognize mushrooms (Wang, 2022).

3.3.3.4 You Only Look Once (YOLO)

You Only Look Once (YOLO) represents a shift in the paradigm of object detection, away from the traditional complex processes towards a single, unified CNN architecture. The fundamental innovation of YOLO is its re-framing of the object detection problem as a single regression task, which is directly derived from the image pixels to the bounding boxes' coordinates and probability of classes (Redmon et al., 2016). This common approach facilitates exceptional speed, which is essential for applications that require rapid analysis, such as autonomous driving or, in our context, the high-throughput classification of mushrooms from field images. Unlike approaches that rely on the sliding window or region proposal (e.g., R-CNN and its variants), YOLO employs a single neural network that is applied to the entire image, this network is divided into a grid and predicted the bounding boxes and probability for each cell in the grid simultaneously. This trainable system's end goal is to have a beneficial ratio of mean Average Precision (mAP) to inference speed, this is ideal for implementing practical agricultural AI solutions (Terven et al., 2023).

The operational pipeline of a standard YOLO model (e.g., YOLOv5/v7/v8 architecture) could be decomposed into the key steps that are illustrated in Figure 5 (Wang & Liao, 2024).

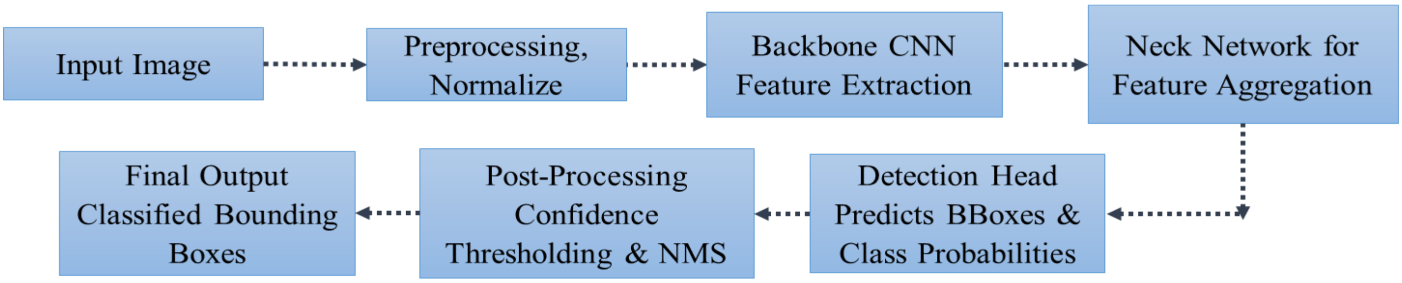

Figure 5. Flow Diagram of the YOLO-based Mushroom Detection and Classification Pipeline.

4. COMPARATIVE ANALYSIS

Table 1 presents a benchmarking analysis of recent research on mushroom classification. It includes references, year of publication, dataset, ML and DL techniques, and accuracy of each analysis. This synthesis provides an overview of methodological advances and demonstrates how different approaches perform across tabular, image-based, and real-world deployment scenarios.

Studies based on tabular datasets, such as the UCI Mushroom dataset, show that traditional ML techniques are already capable of achieving incredibly high performance. DTs, RFs, and ensemble methods have consistently produced high performance. Rahman et al. (2022) combined their models within an IoT farm system, and DTs are the best. Paudel et al. (2022) showed that the RF technique achieves a higher accuracy than the Reduced Error Pruning (REP) Tree technique. Other comparative works highlight the superiority of ensemble methods: Arslan et al. (Arslan et al., 2024) highlighted Extra Trees (ETs) and RF as top performers above 99%, while simpler models like AdaBoost trailed significantly. Even simpler techniques, such as KNNs in Admojo et al. (2024), achieved 99% accuracy on the cleaned UCI dataset. Chen further demonstrated that gradient boosting models such as XGBoost, when evaluated using the Matthews Correlation Coefficient, outperform LightGBM and RF by providing more robust handling of imbalanced classes.

The neural networks have also been used in some studies. Gupta (2022) trained a tuned ANN that achieved 99%, proving that neural models can match or exceed ensemble baselines on categorical attributes. Shilpashree et al. (2025) work, using Kaggle's mushroom dataset, obtained 99.96% with an ANN, surpassing RF slightly. Even more compelling, Eleiwy et al. (2025) developed a one-Dimensional CNN on encoded attributes, which achieved perfect scores across accuracy, precision, recall, and F1, eliminating misclassifications. These results demonstrate that tabular-based mushroom edibility classification is effectively solved, with both ensemble methods and neural networks achieving near-flawless prediction performance.

Some other works are based on image detection and classification of mushrooms. Deep convolutional networks have demonstrated impressive performance, with networks including ResNet-50, GoogLeNet, and hybrids of AlexNet-Inception, and accuracies of 98% to 99.5% have been reported. Ketwongsa et al. (2022) highlighted the balance between speed and accuracy: AlexNet-Inception was the fastest at 98.5%, while ResNet-50 and GoogLeNet performed slightly better at 99.5%, but consumed significantly more computational resources. The development of the PUMA mobile application by Jae Joong Lee et al. (2022) also demonstrated that lightweight CNNs achieve around 99% accuracy on binary edible-poisonous classification. In contrast, the accuracy for three- and five-class problems dropped slightly. The research shows the potential, as well as the limitations, of using models in actual devices.

Zhu et al. (2023) proposed a two-class edibility detection method for mushroom high-quality screening of advanced type based on the network of MobileNetV3-Large with attention and Poly Focal Loss with the highest accuracy of 99.91%. Such an improvement surpassed other state-of-the-art architectures, such as EfficientNetV2-s and ResNet-50, showing that small and efficient architectures are suitable for deployment in resource-constrained settings. On the other hand, undertook a still more daunting assignment, to classify 103 collected from varied habitats. Their CNN achieved an accuracy of 96.7%, with high precision and recall, indicating that deep networks can generalize well with careful data augmentation, even in highly diverse, real-world settings (Bashir et al., 2024).

Industrial and agricultural uses require not only correctness, but also real-time operation. Aghajani et al. (2024) applied YOLOv5 on the inspection of mushroom quality in frozen food processing, which achieved an accuracy of 96% with certain categories being classified as perfect. Similarly, Qi et al. (2025) Mamba-YOLO was designed for auto-picking in a crowded greenhouse environment. The model achieved 98.79% accuracy with a very small latency, which was superior to other detectors, including Faster R-CNN, YOLOv5, YOLOv6, YOLOv7, and YOLOv8, and it was also robust to small, occluded, and clustered mushrooms. These efficiency-driven models also manifest that DT can help achieve automation in industrial inspection and field harvesting by DL methods.

Smaller datasets present unique challenges. Subramania et al. (2024) discovered that SVM-based models performed better than deep neural networks, even though only ~700 images were used and the accuracy of the slowest CNN parse model, ResNet-50 and YOLOv5 trained on the other datasets was 83%, 80% and 79%, respectively. Hybrid-based pipelines that employ deep feature extractors with classical classifiers similarly performed very well. For example, Al Rashid et al. (2025) combined features from B0 EfficientNet with an SVM classifier and obtained 99.5%, which is higher than CNN, VGG16, and ResNet-50. These results demonstrate that hybrid methods can also succeed in small-data settings since they utilize deep features to prevent overfitting.

Some works focus on the importance of preprocessing, data balancing and integration with IoT systems. Aravindhaa et al. (2024) investigated the impact of SMOTE oversampling and showed that simplified classifiers, such as Gaussian Naïve Bayes (GNN), greatly benefited from balanced training data, with a resulting rate of 99.7%. Gradient Boosting and XGBoost also improved with resampling, becoming flat at 95–96%. On a related note, the IoT farm integration from Rahman et al. (2022) demonstrated the role of predictive models in the larger decision-support systems in the real setting of agricultural applications. In another instance, Nithya et al. (2025) trained classifiers on measured physical attributes of the caps, gills, and stalks of the mushrooms and demonstrated that RF and KNN can get about 93 –94% without even using image data.

Table 1. Comparative analysis of LR.

Accuracy Best	ML	Dataset	Year	Reference
100	DT, RF, KNN, LR, SVM, NB, Ensemble (DT + LR + KNN + SVM + NB + RF)	Kaggle Mushroom Dataset (8125 samples, edible vs. poisonous, 21 attributes)	2022	Rahman et al. (Rahman et al., 2022)
100	RF, REP Tree	UCI ML Repository	2022	Paudel et al. (Paudel & Bhatta, 2022)
99	ANN	UCI Mushroom Dataset (8124 instances, 22 attributes, Agaricus & Lepiota family)	2022	Campus et al. (Gupta, 2022)

99.5	AlexNet (CNN), ResNet-50 (CNN), GoogLeNet (CNN), AlexNet + Inception, Module (CNN), AlexNet (R-CNN), ResNet-50 (R-CNN), GoogLeNet (R-CNN), AlexNet + Inception (R-CNN)	Wild Mushroom Dataset (Northeastern Thailand), 2000 images (augmented from 623 images of 5 species)	2022	(Ketwongsa et al., 2022)
97	CNN + Feed-forward NN, Fine-tuned ResNet-152	Collected mushroom images (internet, validated by mycologist): Gyromitra vs. *Morchella* (2-class)	2022	(Lee et al., 2022)
99.91	MobileNetV3, EfficientNetV2-s, ResNet50, VGG16, GoogLeNet, MobileNetV1, MobileNetV2, ShuffleNetV2×1	10,991 shiitake mushroom images (collected in Jilin, China; categorized into Grade I, II, III)	2023	(Zhu et al., 2023)
94	RF (optimized with GridSearchCV), DT (optimized with GridSearchCV), LR	UCI Mushroom Dataset (8124 samples, 22 attributes, Audubon Society Field Guide)	2023	(Metlek & Çetiner, 2023)
83	AlexNet, YOLOv5, ResNet50, SVM	620 mushroom images (toxic & non-toxic), augmented to ~700	2024	(Subramani et al., 2024)
100	YOLOv5 (object detection, CNN-based)	Images of mushroom samples (Control, Pulse, Continues, Raw)	2024	Aghajani et al., 2024)
99	KNN	Cleaned version of the UCI Mushroom Dataset (Kaggle)	2024	(Admojo et al., 2024)
99.17	RF, Gradient Boosting AdaBoost, ET, Bagging	UCI Mushroom Dataset (cleaned version from Kaggle)	2024	(Arslan et al., 2024)
95.5	XGBoost, RF, DT, LR, GNB, SVM, KNN	Modified Kaggle Mushroom Dataset (based on UCI attributes, 23 species)	2024	(Aravindhaa et al., 2024)
99.96	ANN	Kaggle Mushroom Classification dataset	2024	(Shilpashree et al., 2025)
99	RF			
96.7	CNN	Kaggle Mushroom dataset (103 classes, natural habitat images)	2024	(Bashir et al., 2024)
99.5	Hybrid EfficientNet-B0 + SVM, CNN, VGG16, ResNet50	Custom dataset (Mushroom Development Institute, Savar, Dhaka)	2025	(Al Rashid et al., 2025)
94	KNN, RF	Mushroom dataset (physical features: cap, gill, stalk traits, etc.)	2025	(Nithya et al., 2025)
96	XGBoost, RF, LightGBM	UCI Mushroom Dataset	2025	(Chen, 2025)
98.79	Mamba-YOLO, Faster R-CNN, YOLOv5s, YOLOv6s, YOLOv7, YOLOv8	Self-constructed Shiitake Mushroom Dataset (2,320 images, augmented to 6,960)	2025	(Qi et al., 2025)
85.61	KNN, GNB, RF, DT, LightGBM, SVM	Kaggle – Mushroom Classification (2094 images, 5 classes: *Amanita*, *Suillus*, *Hygrocybe*, *Entoloma*, *Agaricus*)	2025	(Rani & Karegowda, 2025)
100	One-Dimensional -CNN	UCI Mushroom Dataset (8124 instances, 22 features; 3916 poisonous, 4208 edible)	2025	(Eleiwy et al., 2025)

5. CHALLENGES AND LIMITATIONS

Despite significant progress in applying ML and DL to mushroom classification, several challenges remain:

- **Lack of large annotated image datasets:** Most existing studies rely on limited collections (UCI, Kaggle, small field datasets), which restricts generalization to diverse real-world conditions. Large-scale, curated, and annotated mushroom datasets are still scarce.
- **Class imbalance (toxic vs. edible):** In practice, poisonous species are much fewer in number compared to edible ones, leading to skewed datasets. This imbalance often results in models biased toward majority classes, reducing reliability in high-risk cases.
- **Overfitting with small datasets:** Deep architectures trained on limited images tend to overfit rather than generalize robustly, limiting deployment.
- **Need for domain knowledge:** Accurate mushroom identification often requires expert mycological knowledge (odor, spore prints, habitat context) beyond visual cues, which current AI systems rarely integrate.

6. FUTURE DIRECTIONS

To overcome these challenges, future research may consider the following directions:

- **Real-time mobile recognition apps:** Development of lightweight CNNs, MobileNets, or YOLO-based detectors optimized for smartphones and IoT platforms will enable farmers, food inspectors, and consumers to identify mushrooms instantly in the field.
- **Hybrid models (ML+expert systems):** Combining data-driven ML/DL methods with expert knowledge (rules, ontologies, or symbolic AI) could yield more interpretable & reliable systems for high-risk edibility prediction.
- **Expansion of fungal databases with AI integration:** Creating and sharing large, standardized fungal image and attribute repositories, enriched with metadata (geolocation, environmental conditions), will facilitate cross-dataset training and benchmarking. AI can further assist in automated annotation and validation.
- **Multimodal fusion and domain adaptation:** Integrating images, sensor data (humidity, soil conditions), and morphological attributes, while employing domain adaptation methods, can help models generalize across unseen environments and species.
- **Explainability and transparency:** Building explainable AI tools (e.g., saliency maps, interpretable ML) will improve trust in real-world applications, particularly in food safety and medical contexts.

7. CONCLUSION

This review has offered a broad integration of ML and DL methods used on mushroom classification and edibility. The ease of learning has enabled classical ML algorithms, including DT, RF, and SVM, to narrow their accuracy gap against the tabular datasets to perfect values, while DL architectures such as CNNs, transfer learning models, and YOLO-based detectors have achieved impressive results on image classification and real-time detection. Hybrid methods, where the deep features are fused with classical classifiers, lead to even more significant improvements when data is limited. However, problems still remain, such as inadequate annotated data sets, unbalanced classes and a lack of generalization to practical scenarios. Solving these challenges will necessitate a collective undertaking in dataset curation, multimodal data integration, and the development of light-weight, explainable, and real-time systems. ML and DL have an enormous potential in improving systems for recognizing mushrooms. With further development in multimodal learning, dataset growth, and AI-enabled mobile deployment, the next generation of intelligent tools may be transformative for agriculture, ecology, and food safety.

Ethical Statement

Not Applicable.

Conflicts of Interest

The authors declare no competing interests.

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