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AI applications in the mushroom industry: present applications, open-data evidence, and future scenario

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ABSTRACT

The mushroom industry is undergoing a transformation from experience to sensors and data and increasingly autonomous production, thanks to artificial intelligence (AI). In this paper, the author summarizes recent mushroom-related applications of AI, and proposes an empirical model that can be used to measure AI adoption among mushroom actors. The proposed primary data component involves a cross-sectional questionnaire of growers, processors, traders, extension and the agritech professionals and presumes the use of an SPSS workflow with reliability, exploratory factor analysis, descriptive statistics, correlation, multiple regression and analysis of variance. Since there was no actual respondent-level primary data provided with the request, primary survey results are not fabricated. The paper, however, features an open-access reproducible section of results, based on the UCI Mushroom dataset and published open-access classification evidence. There are 8124 observations and 22 categorical predictors, with 51.8% of the observations being edible and 48.2% poisonous. When addressing the dominant toxicity discriminator, published feature selection evidence shows that odor is the most important. For models that use LASSO-based linear regression, K-nearest neighbor, and XGBoost, published evidence reports AUC scores of 0.977, 0.989, and 0.999, respectively. The mushroom sector review last year revealed that computer vision was the most widespread digital technology in mushroom research, followed by hyperspectral imaging and Internet-of-Things sensing. The paper says that the next step in the development of the industry will be the combination of multimodal sensing, edge AI, digital twins, federated learning, and autonomous robotics. The central managerial message is that the accuracy of the model is not enough; it must be also be affordable, interoperable, explainable, and have a reliable connection with the farms and skills as well as proven farm-level benefits.

Keywords: Artificial intelligence, Mushroom industry, Smart farming, Computer vision, IoT, Robotic harvesting, SPSS, Digital twin, Open data

1. Introduction

Mushroom production is a highly specific type of CEA where small changes in temperature, relative humidity, CO₂, ventilation, substrate quality, contamination and time of harvest can result in significant changes in yield and market quality. This makes it in all ways an exceptionally well suited sector for information-centered administration. In recent years, various reviews have been written that clearly outline the shift from manual to smart mushroom cultivation, which integrates environmental sensors, imaging systems, machine learning and robotics (Yin *et al.*, 2022; Jacob *et al.*, 2025; Yang *et al.*, 2026) [2, 1, 3]. The ongoing debates on sector growth in India, like those elsewhere, also focus on mechanisation, computerisation of climate control, better post harvest technology and increased technical support for farmers (Thakur *et al.*, 2025) [4].

As of now, there are five operational areas for which AI is being used. Internet-of-Things (IoT) systems record continuously the temperature, humidity, CO₂ and other microclimate parameters and are able to switch on ventilation, fogging or cooling systems. Second, computer vision and deep learning is used to classify mushroom species, to detect toxic and diseased mushrooms, to track the growth stages and to estimate the maturity of mushrooms. Third, hyperspectral and multispectral imaging offer as well non-destructive measures of browning, freshness and quality. Fourthly, machine vision is used more and more to direct robotic harvesting and automated grading. Fifth, predictive models may aid in yield estimation, energy management, optimization of the production environment and production planning (Wieme *et al.*, 2022; Rahman *et al.*, 2022; Zhong *et al.*, 2024; Shui *et al.*, 2026) [6, 5, 7, 8].

The uptake of technology in the industry isn't solely reliant on algorithm accuracy. Adoption can be influenced by a range of factors including farm size, cost, digital skills, connectivity, perceived usefulness, ease of use, trust, compatibility with cultivation activities and the ability to access service support. The logic of Technology Acceptance Model suggests that perceived usefulness and ease of use are the factors influencing technology acceptance (Davis, 1989) [9], while Unified Theory of Acceptance and Use of Technology emphasizes on performance expectancy, effort expectancy, facilitating conditions and social influences (Venkatesh *et al.*, 2003) [10]. Research into these perspectives is important for the mushroom industry be

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cause most farms are small and/or medium scale and would not consider implementing expensive automation without a definite ROI. For this reason, the aim of this paper is two-fold. The first one is to explore the current and future landscape of AI in the mushroom sector. The first one is to analyse the current and future landscape of AI in the mushroom industry. The latter is to offer an empirically sound primary-survey design that can be put into the SPSS software package. In order to maintain the integrity of research, the numerical results here reported are only from transparent open-access sources; no fictional field survey is presented as real primary data is given.

2. Present applications of AI in the mushroom industry

Computer vision is the area with the most focus on AI research. In 2026, 114 papers were reviewed, resulting in 63 computer-vision papers, 28 hyperspectral-imaging papers and 23 papers about IoT-sensors. The same review noted research focusing on *Agaricus bisporus*, *Pleurotus ostreatus* and *Lentinula edodes*, indicating that the development of technology is following the main cultivated species (Yang *et al.*, 2026) [3]. The benefits of computer vision lie in the fact that mushrooms can be described in visible properties, such as cap shape, colour, surface texture, cluster geometry and maturity, which can be captured at a low cost using RGB or smartphone cameras.

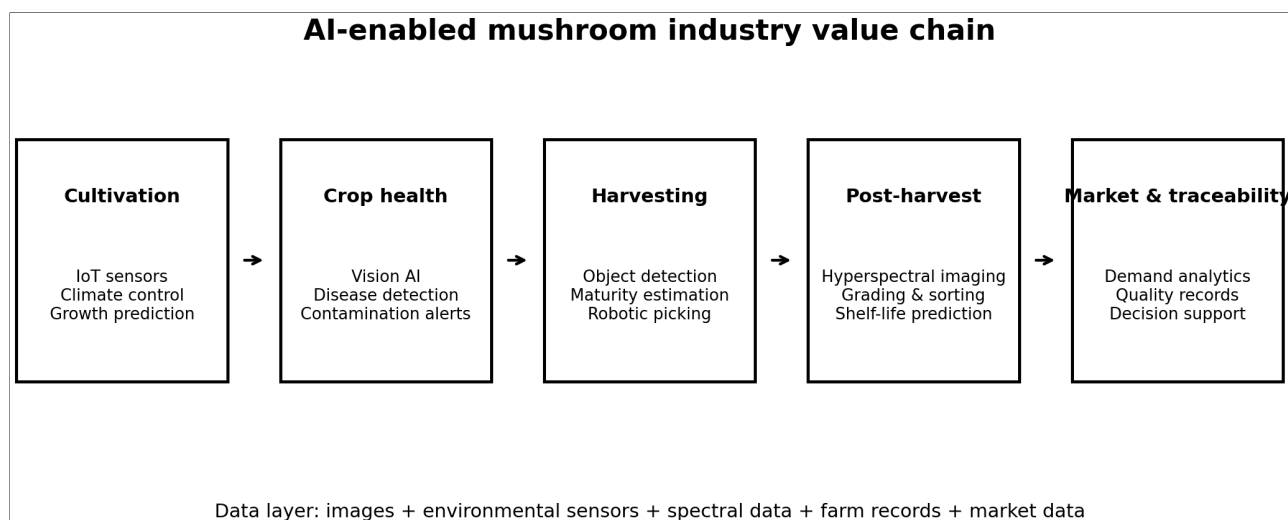


Figure 1. AI-enabled mushroom industry value chain (original synthesis).

One of the most mature (but not the most obvious) AI tasks is species and toxicity classification. Edible and poisonous mushrooms have been classified using convolutional neural networks (CNNs), residual networks, vision transformers and hybrid machine-learning pipelines (Ketwongsa *et al.*, 2022; Lee *et al.*, 2022; Wang, 2022; Bashir *et al.*, 2024; Ozsari *et al.*, 2024; Zhao *et al.*, 2026) [12, 13, 14, 11, 15, 16]. These tools can help decrease the need for expert visual identification, but should not be used to replace toxicological or taxonomic confirmation of professional safety when dealing with humans. Additional research on the UCI dataset with the aim of feature selection also shows that the odor is always a key variable carrying strong predictive information, and that relatively few morphological and organoleptic variables tend to do so (Ortiz-Letechipia *et al.*, 2024) [17].

Smart cultivation systems combine sensing, connectivity and control. Smart (or IoT) farm systems were developed for growing oysters, shiitake mushrooms and button mushrooms to track environmental parameters and to program the automatic control of ventilation, humidification and other interventions (Rahman *et al.*, 2022; Rukhiran *et al.*, 2023; Irwanto *et al.*, 2024; Elewi *et al.*, 2024) [5, 19, 20, 18]. Small producers are especially concerned with low cost architectures, since the economic benefit of AI will depend on whether the sensors and controllers can be installed and serviced at a reasonable cost. Even a basic automation system such as PLC or wireless control system demonstrates the benefits of more consistency and less manual labor that can be used for routine monitoring (Thong-un *et al.*, 2022) [21]. Other high value applications include disease and contamination detection. In dense controlled settings, crop losses may be more rapid and sometimes human scouting can only detect symptoms after crop spread has started. New deep-learning systems are able to recognize mushroom diseases from photos and now even use models via mobile apps. For instance, OysterMushNet is an ensemble of models EfficientNetB0, DenseNet201, and ResNet50V2, which achieves 98.8% model accuracy on a self-collected dataset of images, and is mobile optimized and provides communication between farmer and

agronomist (Guragain *et al.*, 2026) [22]. The pre-trained deep networks are used for *Agaricus disease* classification (Albayrak *et al.*, 2025) [23], and deep-learning methods are used for the detection of oyster mushroom disease (Shilpashree *et al.*, 2025) [24].

Spectral imaging and machine vision are well suited to post harvest quality control. Hyperspectral imaging can be used to identify pre-human eye perceptible quality deterioration, such as reflectance signatures associated with browning, moisture and tissue change (Gowen *et al.*, 2008; Taghizadeh *et al.*, 2011; Mollazade, 2017; Nazir *et al.*, 2022) [25, 26, 27, 28]. The quality classification and automated size grading of shiitake have also been automated by deep-learning systems (Liu *et al.*, 2022; Shui *et al.*, 2026) [29, 8]. These techniques help to achieve good grading, minimise subjectivity and can link quality grades directly to packing lines.

Robotic harvesting is moving out of the lab and into the commercial arena. Button mushrooms have a small size, high density, and are easily damaged, which makes them difficult to detect by robot. Now machine-vision systems are able to identify individual mushrooms, estimate the size and position, determine the picking sequence and guide the compliant grippers (Huang *et al.*, 2021; Ji *et al.*, 2024; Zhong *et al.*, 2024; Ma *et al.*, 2025) [30, 31, 7, 32]. In recent years, various systems have been developed that combine the harvesting, cutting and grading processes, and bio-inspired manipulators, that mimic manual harvesting work to minimize damage to the trees (Gu *et al.*, 2026; Ding *et al.*, 2026) [34, 33]. Spatial information and clustering are also used in the decision making algorithms to identify efficient picking strategy (Mahnan *et al.*, 2026) [35].

AI is also increasingly being used in production planning, phenotyping and breeding. The automation of phenotyping can automatically measure the cap dimension, cap color, texture, and developmental stage and cluster architecture in much shorter time than manual scoring, providing larger and more standardized datasets to choose desirable strains. Machine-learning models can link environmental histories with yield and quality and energy outcomes and enable managers to use alternative climate-control strategies, not just fixed set points,

at the operational level. The modelling concept of sustainability is further expanded in the field of energy use, emissions and environmental cost (Nabavi-Pelesaraei *et al.*, 2023) [36]. The use of AI in foodomics also demonstrates its capability to ensure the authenticity and traceability of food products, particularly in premium and organic sectors, where authenticity is a key consumer expectation, and mislabeling is a significant concern (Vunduk *et al.*, 2024) [37]. These appli-

cations not only extend the notion of AI in mushroom cultivation but also serve as a platform for merging biological, environmental, and commercial data. Therefore, there is a need to evaluate industry readiness at the organizational level, such as data capturing practices, skills of the staff, equipment compatibility, and ability to interpret the results of the models in a timely fashion to take farm actions.

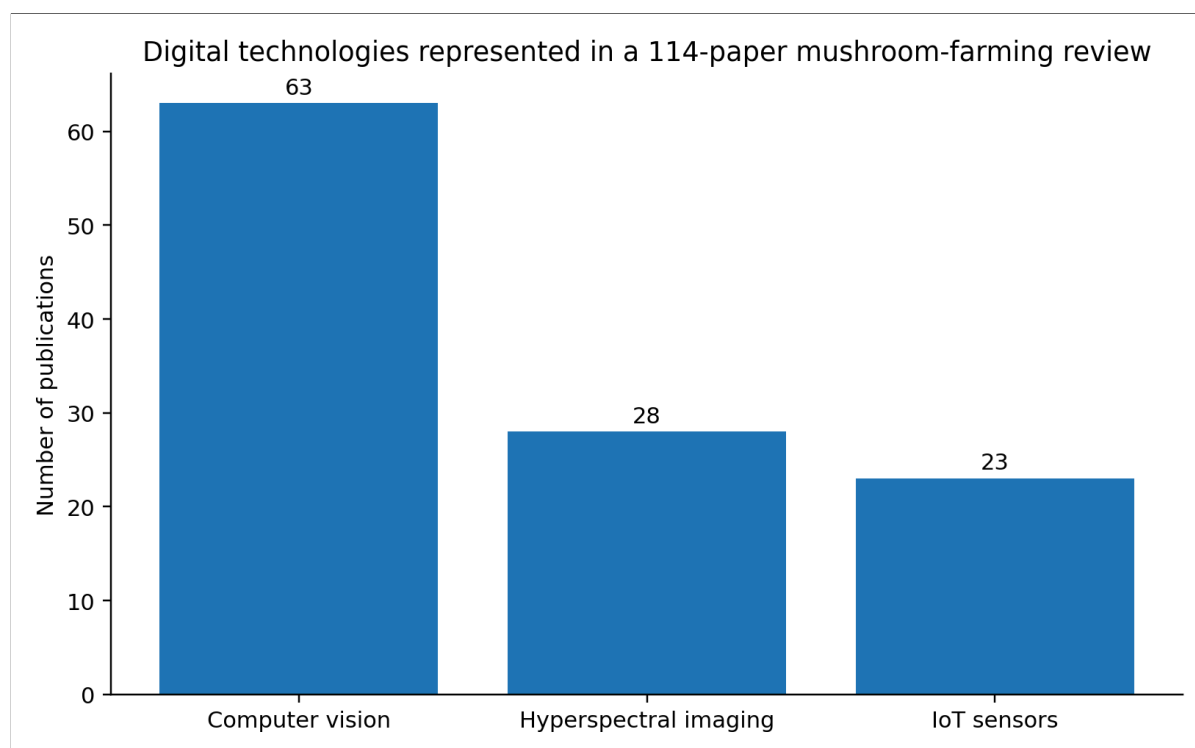


Figure 2. Distribution of major digital technologies in the 114-paper review by Yang *et al.* (2026) [3].

Table 1. Current AI application areas across the mushroom value chain

Industry stage	Data source	Typical AI/analytics	Operational outcome
Cultivation	Temperature, RH, CO ₂ , substrate and image data	Time-series prediction, fuzzy control, anomaly detection	Stable microclimate; reduced manual monitoring
Crop health	RGB/mobile images; environmental records	CNN/transfer learning; object detection	Earlier disease/contamination alerts
Identification	Macroscopic traits and images	CNN, ViT, KNN, XGBoost, logistic models	Species/toxicity decision support
Harvesting	RGB-D/depth images and spatial coordinates	YOLO, segmentation, path planning	Automated picking; labor substitution
Post-harvest	RGB, video, hyperspectral data	Classification, regression, machine vision	Objective grading; shelf-life/quality assessment
Management	Farm records, energy and production data	Forecasting and decision-support models	Yield, resource and scheduling optimization

3. Future scenario: from smart monitoring to autonomous mushroom farms

The next generation of digitalization will not only feature individual AI applications, but also cyber-physical systems. Recently, some reviews suggest that automated growth monitoring can be achieved with the combination of IoT sensors and imaging, vision-based perception for robotic harvesting, portable hyperspectral tools for quality and disease detection, and digital farm/twin models that simulate the farm in software (Yang *et al.*, 2026) [3]. The research of deep learning also suggests that the fusion of multiple modalities, deployment on the edge, and cross-modal self-supervised learning and federated frameworks are effective ways to deal with small data and poor model generalization.

The mushroom cultivation in particular is dynamic and these digital twins are of special interest. The twin can continuously process sensor data, estimate the developmental state of the crop, simulate the results of changing the ventilation, humidity, temperature parameters and/or the scheduling of harvest operations before the change is actually carried out physically. The twin is then used for a closed-loop decision-making architecture when paired with actuators. In a more advanced implementation, camera and sensor streams would be fed to edge AI for real-time detection and higher-level models would be used to update growth forecasts, labor needs, energy strategies.

Edge AI will be needed when there is no internet connection or if a farm can't keep streaming high volume video data. Lightweight CNNs and quantized models can be deployed locally on local devices or on smart phones, thus decreasing the latency and cloud cost. The 2026 real-time grading system developed by Shui *et al.* provides an exam-

ple of this: The model was optimized, which not only bolstered the accuracy of the grading process but also boosted processing speed. The same deployment principles can enable smaller growers to be more easily able to recognize and monitor the growth of disease. Data fragmentation is one of the problems that could be addressed by federated learning in the sector. Farms might not need to transfer raw proprietary production images or production records to a central server for training a shared model. This would enable models to learn from the variety, climate and facility data and at the same time ensure certain level of data privacy. Federated systems, however, do need to have a common set of data definitions, calibration protocols and governance. Shared models may fail to resolve inconsistencies, because they do not have consistent definitions of maturity, disease severity, quality grade, and environmental events.

Advisory services could also be impacted by generative and foundation-model. Context-aware troubleshooting suggestions might be achieved by multimodal assistants, which could integrate images, sensor histories and cultivation manuals. Such systems should be created as decision support systems, not as decision making bodies particularly for toxicity identification and disease-management recommendations. The importance of explaining, confidence estimates and escalation to agronomists/mycologists will remain important. Last but not least, autonomous harvesting is likely to evolve in a piecemeal fashion. Completely replacing human harvesters in dense and variable mushroom beds is a challenge, whereas some mushroom picking systems will automate repetitive picking areas and/or size grading and/or transport, while exceptions are left to humans. Modular automation will thus be crucial for economic success and is possible in stages.

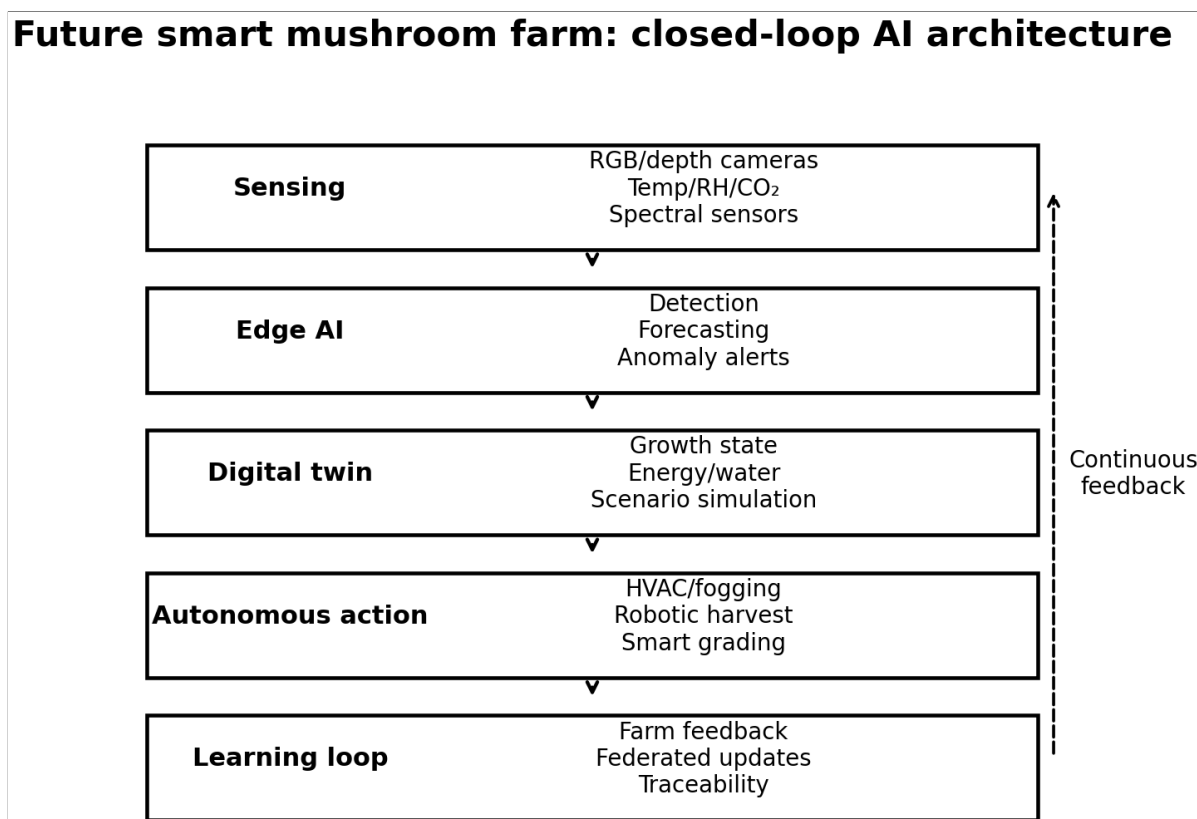


Figure 3. Proposed closed-loop architecture for future smart mushroom farms (original synthesis).

4. Research objectives, questions, and hypotheses

4.1 Research objectives

- Assess the current level of awareness and adoption of AI-enabled technologies among mushroom-industry stakeholders.
- Identify the perceived operational benefits of AI for cultivation control, disease management, harvesting, grading and decision support.
- Examine technological, financial, organizational and skill-related barriers to AI adoption.
- Test the relationships between perceived usefulness, ease of use, digital readiness, trust, cost barriers and AI adoption intention.
- Evaluate whether AI adoption intensity is associated with perceived operational performance and whether adoption differs by enterprise size or stakeholder group.
- Develop evidence-based priorities for future smart mushroom-farm technologies.

4.2 Research questions

- RQ1: What AI applications are currently known, used or planned by mushroom-industry stakeholders?
- RQ2: Which benefits and barriers most strongly shape willingness to adopt AI-enabled technologies?
- RQ3: Which organizational and perceptual factors significantly predict AI adoption intention and adoption intensity?
- RQ4: Which future technologies—edge AI, digital twins, multi-modal sensing, robotics or federated learning—are considered most valuable for the mushroom industry?

4.3 Hypotheses for the primary survey

- H1: AI awareness is positively associated with AI adoption intention.
- H₂: Perceived usefulness is positively associated with AI adoption intention.
- H3: Perceived ease of use and digital readiness are positively associated with AI adoption intention.
- H4: Perceived cost and implementation complexity are negatively associated with AI adoption intention.

- H5: Trust in AI outputs and perceived data quality are positively associated with AI adoption intention.
- H6: AI adoption intensity is positively associated with perceived operational performance.
- H7: Mean AI adoption intensity differs significantly across enterprise-size or stakeholder categories.

5. Methodology

The study is designed as a cross-sectional quantitative survey supported by an open-access technical benchmark. The primary-data component is intended to measure industry adoption, while the benchmark component demonstrates the analytical value of AI using a transparent public mushroom dataset. The two components answer different questions and should not be merged statistically.

5.1 Primary-data methodology (in pointers)

- Research design: Cross-sectional, explanatory quantitative survey with an optional follow-up interview phase for interpreting barriers and implementation experiences.
- Target population: Commercial and semi-commercial mushroom growers, processors/packers, traders/retailers, extension officers, researchers and agritech/service providers involved with mushroom production.
- Sampling strategy: Stratified recruitment by stakeholder category; use proportionate random sampling where a reliable stakeholder list exists and stratified purposive recruitment where no complete sampling frame exists. The final paper should state the actual frame and recruitment route used.
- Target sample: Approximately 300 valid responses. This is adequate for descriptive analysis, scale reliability, exploratory factor analysis and multiple regression with the proposed number of predictors, while remaining feasible for a specialized agricultural sector.
- Instrument: Structured questionnaire using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree), plus demographic and enterprise variables and check-box questions on specific AI applications.
- Core constructs: AI awareness (AWARE), perceived usefulness (PU), perceived ease of use (PEOU), digital readiness (READY), cost/complexity barrier (COST), trust/data quality (TRUST), adoption intention/intensity (ADOPT) and perceived operational performance (PERF).

- Pilot testing: Conduct with 25–30 stakeholders not included in the final sample; revise ambiguous wording and calculate preliminary reliability.
- Ethics: Obtain informed consent, avoid personally identifying information unless necessary, and explain voluntary participation and withdrawal rights.
- SPSS software: IBM SPSS Statistics (version 29 or current institutional version). Use two-tailed tests with $\alpha = .05$ and report effect sizes and 95% confidence intervals where available.
- Data cleaning: Check duplicates, impossible values, missingness, straight-lining and outliers. Reverse-code negatively worded items before computing scale means.
- Reliability: Cronbach's alpha for each multi-item construct; $\alpha \geq .70$ is a conventional adequacy target, interpreted alongside item-total correlations and construct content.
- Construct validity: Exploratory factor analysis using principal-axis factoring and oblique rotation; report KMO, Bartlett's test, communalities and factor loadings. Avoid retaining items solely to maximize alpha.
- Descriptive analysis: Frequencies/percentages for categorical variables; means and standard deviations for scale scores; report current AI-use categories separately.
- Bivariate analysis: Pearson correlations for approximately continuous scale scores when assumptions are acceptable; use Spearman correlations when distributions are markedly non-normal or ordinal treatment is preferred.
- Multivariate analysis: Multiple linear regression predicting adoption intention from awareness, usefulness, ease of use, readiness, cost barriers and trust. Examine tolerance/VIF, residual normality, homoscedasticity and influential cases.
- Performance model: Regress perceived operational performance on AI adoption intensity while controlling for enterprise size and stakeholder category, interpreting the design as associational rather than causal.
- Group comparison: One-way ANOVA (with Welch correction if variances are unequal) for adoption differences across enterprise-size/stakeholder groups; use Games–Howell post hoc tests when appropriate.

Table 2. Proposed constructs and questionnaire indicators

Construct	Example indicators	Expected direction
AI awareness	I understand current AI uses in mushroom production; I can distinguish AI tools from basic automation.	Positive
Perceived usefulness	AI can improve crop monitoring; AI can improve grading consistency; AI can reduce avoidable losses.	Positive
Perceived ease of use	AI tools can be learned without excessive effort; interfaces are understandable.	Positive
Digital readiness	Reliable sensors/connectivity are available; staff can use digital systems; records are digitized.	Positive
Cost/complexity barrier	Initial cost is too high; maintenance is difficult; integration is complex.	Negative
Trust/data quality	I trust AI when confidence and evidence are shown; farm data are accurate enough for AI.	Positive
Adoption	We currently use or plan to use AI-enabled tools; AI is part of farm technology planning.	DV
Operational performance	AI use is associated with better consistency, faster decisions, quality control or labor productivity.	Outcome

(continued on next page)

Table 3. Hypothesis-to-SPSS analysis map

Hypothesis	Dependent variable	Main predictor/test	SPSS procedure
H1	Adoption intention	AI awareness	Pearson correlation + multiple regression
H ₂	Adoption intention	Perceived usefulness	Multiple regression
H3	Adoption intention	Ease of use; digital readiness	Multiple regression
H4	Adoption intention	Cost/complexity barrier	Multiple regression (expected negative beta)
H5	Adoption intention	Trust/data quality	Multiple regression
H6	Operational performance	Adoption intensity	Hierarchical/standard multiple regression
H7	Adoption intensity	Enterprise/stakeholder groups	One-way ANOVA or Welch ANOVA

6. Open-access data and benchmark analysis

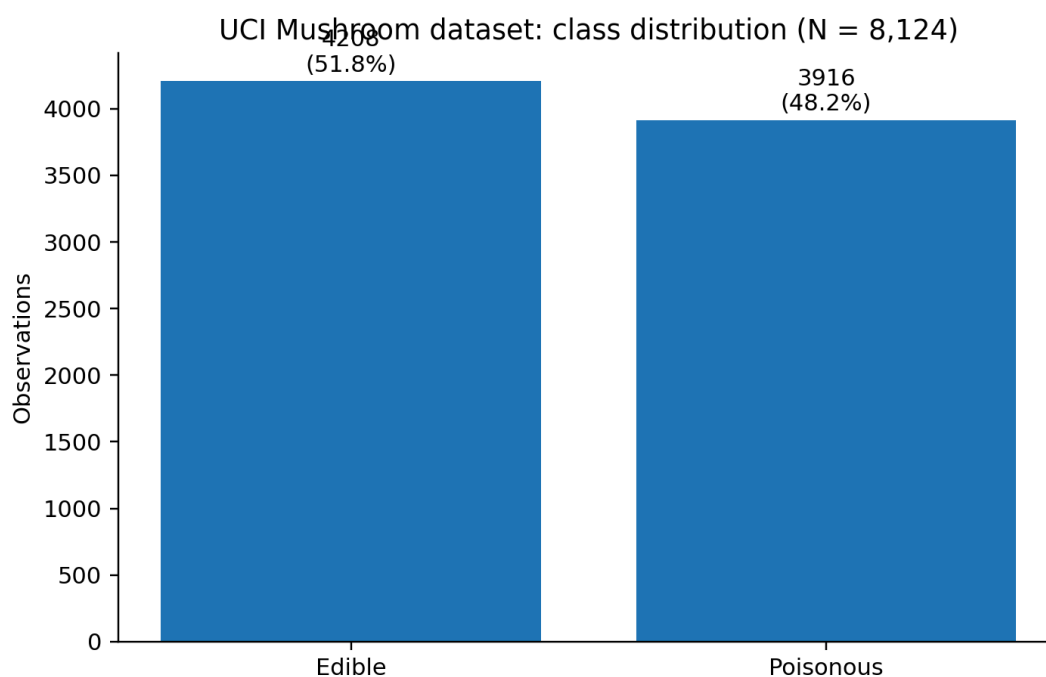
The UCI Mushroom dataset is not used as a dataset for the proposed stakeholder survey but is used as a technical benchmark for the completed numerical analysis in this paper. 8124 observations of the Agaricus/Lepiota-family, classified edible or poisonous, described by 22 categorical attributes, are present in the dataset. It is licensed under CC BY 4.0 and has DOI 10.24432/C5959T (1987/2023 record for the UCI Machine Learning Repository). The dataset is appropriate for showing the predictive ability of mushroom's structured characteristics, but not for measuring the farm adoption, profitability or the attitudes of the stakeholders.

The benchmark is summarized with class frequencies and open-access results from feature-selection and model-validation results from Ortiz-Letechipia *et al.* (2024) [17]. They randomly split the data into training and blind-test sets, use LASSO and genetic-algorithm feature

selection, and compare logistic regression, KNN and XGBoost. Reporting these published metrics give repeatable evidence without having to create primary survey responses.

Table 4. Open-access UCI Mushroom dataset profile

Characteristic	Value
Observations	8,124
Predictor variables	22 categorical mushroom characteristics
Outcome	Edible vs. poisonous
Edible class	4,208 (51.8%)
Poisonous class	3,916 (48.2%)
Missing values	2,480 values, concentrated in stalk-root
License	CC BY 4.0
Dataset DOI	10.24432/C5959T

**Figure 4.** Class distribution in the UCI Mushroom dataset.

7. Results

As a result of the open access evidence, the following practical findings are produced. First of all the balance between "edible" and "poisonous" observations in the UCI benchmark is almost even: 4208 observations (51.8%) are edible, 3916 observations (48.2%) are poisonous. This balance helps to minimize the chance that the classification accuracy achieved is of a high level, but only as a result of predicting the most frequently occurring class. However, there are some important limitations with the data set: 2,480 values are missing for

the field "stalk-root" and thus decisions for this field in the pre-processing should be summarized separately.

Second, evidence from feature selection indicates that not all the mushroom attributes observed are equally important. The importance score for odor was 99.99% under the LASSO analysis, and genetic algorithm picked up odor, spore-print color and habitat, while gill size was 73.7% and stalk shape was 39.9% under the LASSO analysis. This is a general principle in the central AI industry: Wherever possible, good feature engineering, using biologically relevant features, can simplify the model without sacrificing predictive accuracy.

Third, the discriminatory performance of the classification results is very high in combination with modern algorithms, with the features selected. Logistic regression, KNN and XGBoost models, when using Lasso selected features, had an AUC of .977, .989 and .999, respectively. For the experimental split, the published confusion matrices show that XGBoost achieves perfect test classification. These outcomes show that this is technically possible, but cannot be taken for granted when applying this to field images, new mushrooms or new geographic regions or commercial mushroom growing conditions. External validation, domain-specific safety controls are still required.

The literature-level analysis also reveals in which area of the sector the research effort is being invested. Overall, Yang *et al.* (2026) [3] noted 114 publications that they summarized, with computer vision accounting for 63 publications, hyperspectral-imaging for 28, and IoT-sensors for 23. Computer vision thus seems to be the technology centre of gravity at the moment, and IoT is focused at cultivation, with hyperspectral imaging focused at post harvest quality applications. The pattern indicates that integrated systems in the future will not take the place of these modalities but will be used in combination.

Table 5. Selected feature-importance evidence from open-access toxicity-classification research

Feature	Reported importance/role	Interpretation
Odor	99.99% importance in LASSO analysis	Dominant discriminator in the benchmark
Gill size	73.7%	Strong structural predictor
Stalk shape	39.9%	Moderate predictor
Spore-print color	Selected by genetic algorithm	High-value categorical discriminator
Habitat	Selected by genetic algorithm	Ecological context contributes information

Table 6. Published model performance using LASSO-selected features

Model	AUC	Sensitivity	Specificity
Logistic regression	.977	.960	.951
K-nearest neighbors	.989	.976	.937
XGBoost	.999	1.000	1.000

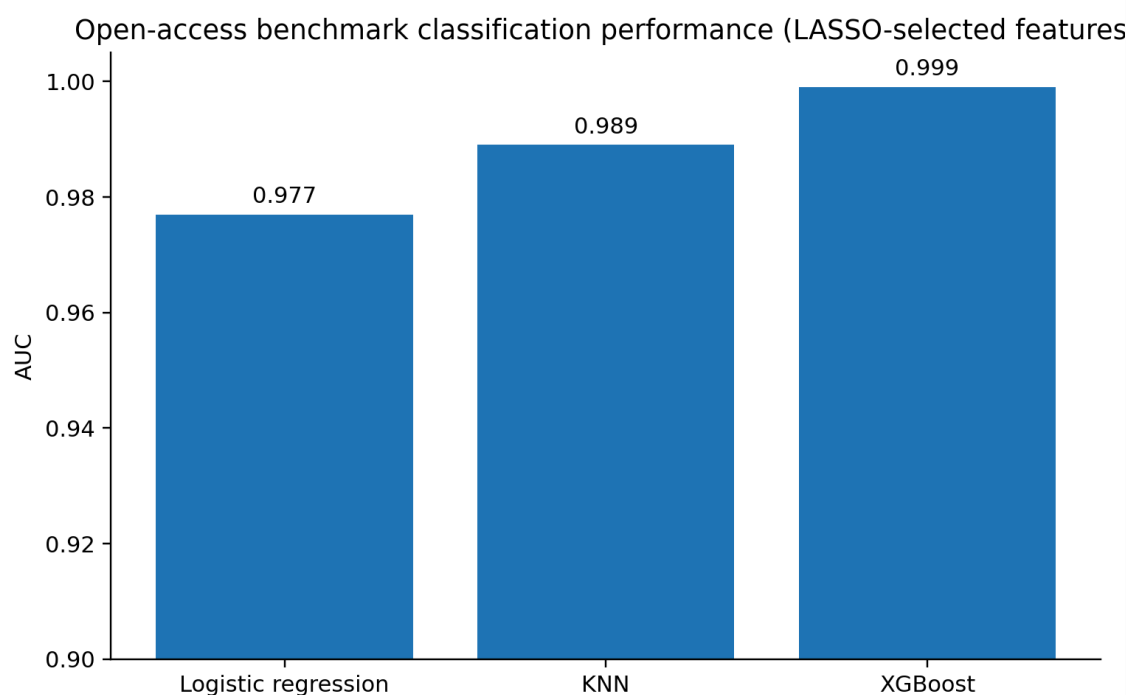


Figure 5. AUC reported by Ortiz-Letechipia *et al.* (2024) [17] for LASSO-selected features.

8. Discussion

The evidence suggests that AI mushroom applications are not limited to mushroom species identification. It's turning into an end-to-end production technology. Environmental control systems deal with the sensitivity of fungi to the microclimate; computer vision deals with monitoring and identifying the crop and robotics with harvest labor; while spectral imaging deals with post-harvest quality. The strategic opportunity is to link these presently separate tools together as inter-operable systems.

The technical benchmark is an example of what can go wrong and what can go right when using headline accuracy. The near-perfect AUCs on a well-defined categorical benchmark are helpful during algorithm development, but commercial farms also have variations in lighting, overlapping fruiting bodies, dust, water droplets, cultivar, and hardware. There is degradation due to image and sensor drift. So, external validation, calibration, confidence limits and fallback processes need to be incorporated into the field deployment. This is particularly relevant for toxicity classification where a misclassification can have implications for health.

The research on adoptions is also significant. Even when a farmer thinks a given AI model is correct, he/she may refuse it because the cost of installation is high, there is no maintenance support available for the system, or the user interface is not ergonomic. The proposed primary survey translates this problem into measurable constructs. On the expected regression model, perceived usefulness and digital readiness should positively impact the adoption intention, whereas cost/complexity should negatively impact the adoption intention. These expectations are in line with the existing acceptance theory (Davis, 1989, Venkatesh *et al.*, 2003) [9], but need to be validated with real world data and not assumed.

Modularity will probably be important for Indian mushroom enterprises. Small growers are included in the sector along with larger controlled environment operations. The low cost sequence might start with sensors and disease recognition on the smartphone, followed by automated environmental control, quality grading and finally harvesting automation. This structured path means that there is less capital risk, and that it is possible for companies to develop digital skills with less complicated robots before making the jump to more complex ones. Indian mushroom production is also identified as a need for development in the 2025 review, which includes climate control, mechanization, post-harvest systems and training (Thakur *et al.*, 2025) [4]. The future scenario also poses governance issues. Images and production records have commercial value and clarity of ownership, consent and cybersecurity is needed for shared learning between farms. While federated learning can decrease the amount of raw data that needs to be centralized, it doesn't eliminate the governance requirements. Training populations, species coverage, sensor conditions, and known failure modes and update history should be identified in model documentation. As AI goes beyond the advisory phase to autonomous control and robotic action, these practices will acquire greater significance.

9. Implications for industry and policy

- Encourage development and adoption of interoperable sensor and data standard to allow environmental, image and production data to be merged between equipment vendors.
- Support for shared, ethically controlled image and time-series data sets of significant cultivated species, diseases, maturity stages and region conditions.
- Foster low-cost edge-AI solutions and small and medium mushroom enterprises' interfaces that are available in the local language.
- Provide public extension systems and agronomists with AI decision-support tools instead of a fully automated piece of advice without intervention.
- Produce field validation of harvesting robots and grading systems based on commercial assessments including damage rate, kg/hr, downtime, maintenance cost and payback.
- Construct short technical training modules for growers/staff for sensor calibration, data collection with images, model interpretation, and digital data record keeping.

10. Limitations

One of the limitations of the present paper is intended: No primary survey file of respondents has been provided; therefore, no inferential statistics for stakeholder adoption are reported. If the empirical contribution is fabricated, then it is not empirical. The primary-data section should then be considered as a complete protocol that is to be followed once the actual responses have been obtained. Additionally, the open-access UCI benchmark is not based on commercial production information, but rather on structured hypothetical mushroom descriptions; hence, it cannot quantify the effects of farm productivity or economic returns. Further, the published AI research is conducted on various species, various train-test splits and various performance metrics, making it difficult to directly compare studies.

11. Conclusion

The mushroom industry has seen some of the more successful mushroom AI applications now move beyond the point of just classification experiments and into smart cultivation, mobile mushroom disease diagnosis, machine-vision mushroom grading and robotic mushroom picking. Computer vision has the best current capacities, and the IoT sensors and hyperspectral imaging have complementary roles in cultivation and quality control. The open access benchmark evidence shows that mushroom characteristics can produce extremely high classification performance, but this needs to be tested in varying real-world settings for commercial deployment.

Environmental sensors, cameras, spectral devices and production records are likely to be connected with edge AI and digital twins that in turn will control climate actuators, robots to harvest mushrooms and grading lines, in a future closed-loop mushroom farm. The industry can learn across farms if they adopt federated learning and/or multimodal models without having to centralize all raw datasets. The focus of the research question is thus moving from 'Can AI classify or detect mushrooms?', to 'Under what economic, organizational and agronomic conditions is AI capable of bringing reliable value at farm scale?'. A primary survey and SPSS analysis plan has been proposed that will give a robust path to answer that question using actual stakeholder data.

References

1. Jacob MS, Xu A, Qian K, Qi Z, Li X, Zhang B. Artificial intelligence in edible mushroom cultivation, breeding, and classification: A comprehensive review. *Journal of Fungi*. 2025;11(11):758.
2. Yin H, Yi W, Hu D. Computer vision and machine learning applied in the mushroom industry: A critical review. *Computers and Electronics in Agriculture*. 2022;198:107015.
3. Yang K, Argyropoulos D. Towards smart mushroom farming: A comprehensive review of data, sensors, robotics and artificial intelligence. *Smart Agricultural Technology*. 2026;14:102129.
4. Thakur MP, Singh HK, Shukla CS. Current status and future prospects of mushroom cultivation and research in India: A review. *CABI Agriculture and Bioscience*. 2025;6(1):0056.
5. Rahman H, Faruq MO, Hai TBA, Rahman W, Hossain MM, Hasan M, Islam S, Moinuddin M, Islam MT, Azad MM. IoT enabled mushroom farm automation with machine learning to classify toxic mushrooms in Bangladesh. *Journal of Agriculture and Food Research*. 2022;7:100267.
6. Wieme J, Mollazade K, Malounas I, Zude-Sasse M, Zhao M, Gowen A, Argyropoulos D, Fountas S, Van Beek J. Application of hyperspectral imaging systems and artificial intelligence for quality assessment of fruit, vegetables and mushrooms: A review. *Biosystems Engineering*. 2022;222:156–176.
7. Zhong M, Han R, Liu Y, Huang B, Chai X, Liu Y. Development, integration, and field evaluation of an autonomous *Agaricus bisporus* picking robot. *Computers and Electronics in Agriculture*. 2024;220:108871.
8. Shui Q, Miao F, Liu S, Cao L, Jiang H, Lu J. A fast and real-time machine vision evaluation system for size grading of *Agaricus bisporus* based on video. *Food Science & Nutrition*. 2026;14(1):e71328.
9. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*. 1989;13(3):319–340.
10. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. *MIS Quarterly*. 2003;27(3):425–478.
11. Bashir RN, Mzoughi O, Riaz N, Mujahid M, Faheem M, Tausif M, Khan AR. Mushroom species classification in natural habitats using convolutional neural networks (CNN). *IEEE Access*. 2024;12:176818–176832.

12. Ketwongsa W, Boonlue S, Kokaew U. A new deep learning model for the classification of poisonous and edible mushrooms based on improved AlexNet convolutional neural network. *Applied Sciences*. 2022;12(7):3409.
13. Lee JJ, Aime MC, Rajwa B, Bae E. Machine learning-based classification of mushrooms using a smartphone application. *Applied Sciences*. 2022;12(22):11685.
14. Wang B. Automatic mushroom species classification model for foodborne disease prevention based on vision transformer. *Journal of Food Quality*. 2022;2022:1173102.
15. Ozsari S, Kumru E, Ekinci F, Akata I, Guzel MS, Acici K, Ozcan E, Asuroglu T. Deep learning-based classification of macrofungi: Comparative analysis of advanced models for accurate fungi identification. *Sensors*. 2024;24(22):7189.
16. Zhao X, Lin H, Guo Y, Sun N. Classification of mushrooms based on AWPf-ResNet18. *PLOS ONE*. 2026;21(4):e0346589.
17. Ortiz-Letechipia JS, Galvan-Tejada CE, Galván-Tejada JJ, Soto-Murillo MA, Acosta-Cruz E, Gamboa-Rosales H, Celaya Padilla JM, Luna-García H. Classification and selection of the main features for the identification of toxicity in *Agaricus* and *Lepiota* with machine learning algorithms. *PeerJ*. 2024;12:e16501.
18. Elewi A, Hajhamed A, Khankan R, Duman S, Souag A, Ahmed A. Design and implementation of a cost-aware and smart oyster mushroom cultivation system. *Smart Agricultural Technology*. 2024;8:100439.
19. Rukhiran M, Sutanthavibul C, Boonsong S, Netinant P. IoT-based mushroom cultivation system with solar renewable energy integration: Assessing the sustainable impact of the yield and quality. *Sustainability*. 2023;15(18):13968.
20. Irwanto F, Hasan U, Lays ES, De La Croix NJ, Mukanyiligira D, Sibomana L, Ahmad T. IoT and fuzzy logic integration for improved substrate environment management in mushroom cultivation. *Smart Agricultural Technology*. 2024;7:100427.
21. Thong-un N, Wongsaroj W. Productivity enhancement using low-cost smart wireless programmable logic controllers: A case study of an oyster mushroom farm. *Computers and Electronics in Agriculture*. 2022;195:106798.
22. Guragain DP, Shrestha B, Bajracharya I, Sharma N, Ghimire D, Bhat SA. OysterMushNet: A deep learning-based mobile application for real-time mushroom disease detection and agronomist support. *Smart Agricultural Technology*. 2026;13:101735.
23. Albayrak U, Golcuk A, Aktas S, Coruh U, Tasdemir S, Baykan OK. Classification and analysis of *Agaricus bisporus* diseases with pre-trained deep learning models. *Agronomy*. 2025;15(1):226.
24. Shilpashree PS, Chandru V, Ramesh GN, Chetan D. Automated disease detection in oyster mushroom cultivation using deep learning technique. In 2025 3rd International Conference on Smart Systems for Applications in Electrical Sciences (ICSSSES). IEEE. 2025.
25. Gowen AA, O'Donnell CP, Taghizadeh M, Gaston E, O'Gorman A, Cullen PJ, Frias JM, Esquerre C, Downey G. Hyperspectral imaging for the investigation of quality deterioration in sliced mushrooms (*Agaricus bisporus*) during storage. *Sensing and Instrumentation for Food Quality and Safety*. 2008;2(3):133–143.
26. Taghizadeh M, Gowen AA, O'Donnell CP. Comparison of hyperspectral imaging with conventional RGB imaging for quality evaluation of *Agaricus bisporus* mushrooms. *Biosystems Engineering*. 2011;108(2):191–194.
27. Mollazade K. Non-destructive identifying level of browning development in button mushroom (*Agaricus bisporus*) using hyperspectral imaging associated with chemometrics. *Food Analytical Methods*. 2017;10:2743–2754.
28. Nazir A, AlDhaheri M, Mudgil P, Marpu P, Kamal-Eldin A. Hyperspectral imaging based kinetic approach to assess quality deterioration in fresh mushrooms (*Agaricus bisporus*) during postharvest storage. *Food Control*. 2022;131:108298.
29. Liu Q, Fang M, Li Y, Gao M. Deep learning based research on quality classification of shiitake mushrooms. *LWT*. 2022;168:113902.
30. Huang M, He L, Choi D, Pecchia J, Li Y. Picking dynamic analysis for robotic harvesting of *Agaricus bisporus* mushrooms. *Computers and Electronics in Agriculture*. 2021;185:106145.
31. Ji J, Du S, Li M, Zhu X, Zhao K, Zhang S, Ji X. Design and experiment of a picking robot for *Agaricus bisporus* based on machine vision. *International Journal of Agricultural and Biological Engineering*. 2024;17(4):67–76.
32. Ma H, Ding Y, Cui H, Ji J, Jin X, Ding T, Wang J. The application of an intelligent *Agaricus bisporus*-harvesting device based on FES-YOLOv5s. *Sensors*. 2025;25(2):519.
33. Ding T, Zhou Y, Ma H, Ding Y, Cui H. Design and testing of an integrated robot for harvesting, stipe-cutting, and grading of *Agaricus bisporus*. *Sensors*. 2026;26(14):4414.
34. Gu Y, Li B, Lu W. Mushroom (*Agaricus bisporus*) picking robot based on mimicry of manual harvesting. *Computers and Electronics in Agriculture*. 2026;243:111394.
35. Mahnan S, Arthur L, He L, Ghatrehsamani S, Heinemann P, Pecchia J. Development of a decision-making algorithm to identify picking strategies for robotic mushroom harvesting. *Computers and Electronics in Agriculture*. 2026;247:111753.
36. Nabavi-Pelesaraei A, Ghasemi-Mobtaker H, Salehi M, Rafiee S, Chau KW, Ebrahimi R. Machine learning models of exergo-environmental damages and emissions social cost for mushroom production. *Agronomy*. 2023;13(3):737.
37. Vunduk J, Kozarski M, Klaus A, Jadranin M, Pezo L, Todorović N. Preventing mislabeling of organic white button mushrooms (*Agaricus bisporus*) combining NMR-based foodomics, statistical, and machine learning approach. *Food Research International*. 2024;198:115366.
38. Agarwal AK, Khullar V, Agrawal NK. Scalable machine learning for mushroom dataset classification. In 2021 International Conference on Simulation, Automation & Smart Manufacturing (SASM). IEEE. 2021.
39. Al Rashid F, Tarin FH, Rahman MM, Khanam T, Dipto SM, Kibria MG. An efficient deep learning based approach for toxic and edible mushroom classification. In 2025 International Conference on Electrical, Computer and Communication Engineering (ECCE). IEEE. 2025.
40. Aravindhana V, Sanjanaa RJ, Raaj ATM, Rani C, Kumar MR. Advancing sustainability in mushroom cultivation by leveraging IoT and ML techniques. In 2024 3rd International Conference on Artificial Intelligence for Internet of Things (AIIoT). IEEE. 2024.
41. De La Croix NJ, Didacienne M, Louis S, Philander JT, Ahmad T. Internet of Things based controlled environment for the production of shiitake mushroom. In 2022 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS). 2022.
42. Deng J, Liu Y, Xiao X. Deep-learning-based wireless visual sensor system for shiitake mushroom sorting. *Computers and Electronics in Agriculture*. 2018;151:416–425.
43. Farshbaf Aghajani P, Soltani Firouz M, Bohlol P. Revolutionizing mushroom identification: Improving efficiency with ultrasound-assisted frozen sample analysis and deep learning techniques. *Journal of Agriculture and Food Research*. 2024;15:100946.
44. Fawcett T. An introduction to ROC analysis. *Pattern Recognition Letters*. 2006;27(8):861–874.
45. Guragain DP, Shrestha B, Bajracharya I. A low-cost centralized IoT ecosystem for enhancing oyster mushroom cultivation. *Journal of Agriculture and Food Research*. 2024;15:100952.

46. Hou X, Luo C, Chen S, Zhang X, Jiang J, Yang Z, Wang F, Xie X. Progress in research on diseases of edible fungi and their detection methods: A review. *Crop Protection*. 2023;174:106420.
47. Koirala B, Zakeri A, Kang J, Kafle A, Balan V, Merchant FA, Benhaddou D, Zhu W. Robotic button mushroom harvesting systems: A review of design, mechanism, and future directions. *Applied Sciences*. 2024;14(20):9229.
48. Masoudian A, McIsaac KA. Application of support vector machine to detect microbial spoilage of mushrooms. 2013 International Conference on Computer and Robot Vision. IEEE. 2013.
49. Maurya P, Singh NP. Mushroom classification using feature-based machine learning approach. *Proceedings of the 3rd International Conference on Computer Vision and Image Processing*. Springer. 2020:197-206.
50. Moorthi K, Sureshu S, Vasanti G, Mishra A, Gandhewar N, Kalra G. IoT enabled mushroom farm automation based on CNN-BiGRU-CRF method. In 2023 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA). IEEE. 2023.
51. Paudel N, Bhatta J. Mushroom classification using random forest and REP tree classifiers. *Nepal Journal of Mathematical Sciences*. 2022;3(1):111–116.
52. Perera K, Packeeran R, Suriyabandara Y, Rizwan H, Karunasena A, Weerasinghe L. Button mushroom farming using machine learning. *Procedia Computer Science*. 2024;235:1742–1751.
53. Qi K, Yang Z, Fan Y, Song H, Liang Z, Wang S, Wang F. Detection and classification of shiitake mushroom fruiting bodies based on Mamba YOLO. *Scientific Reports*. 2025;15:15214.
54. Singh HD, Patel T, Singh HJ, Pal A. Oyster mushroom farming with IoT and artificial intelligence: A comprehensive review. *Journal of Agricultural Engineering*. 2025;62(2):293–306.
55. Subramani S, Imran AF, Abhishek TTM, Yaswanth J. Deep learning based detection of toxic mushrooms in *Karnataka*. *Procedia Computer Science*. 2024;235:91–101.
56. UCI Machine Learning Repository. Mushroom [Dataset]. 1987.
57. Wagner D, Heider D, Hattab G. Mushroom data creation, curation, and simulation to support classification tasks. *Scientific Reports*. 2021;11:8134.
58. Wibowo A, Rahayu Y, Riyanto A, Hidayatulloh T. Classification algorithm for edible mushroom identification. In 2018 International Conference on Information and Communications Technology (ICOIACT). IEEE. 2018.
59. Zhu F, Zhang W, Li Z, Gao T, Zhao Q. A YOLOv7-based robotic harvesting system for *Agaricus bisporus* using a depth camera. *Turkish Journal of Agriculture and Forestry*. 2025;49(2):380–396.
60. Foffano MOA, Michel RC, Freire DMG, Cavalcanti EDC. Design and evaluation of a compact IoT-enabled microfarm for decentralized urban agriculture applied to the cultivation of *Pleurotus ostreatus* (oyster mushroom). *Sustainability*. 2025;17(22):10332.

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