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Brief Communication

AI-mediated Risks and Real-life Challenges in Mushroom Foraging

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Abstract

The rise of AI-based mushroom identification applications impacts foraging despite significant risks from relying solely on AI-generated advice. Popular AI-based mushroom identification tools were tested using 100+ photos of nearly 60 species, taken in real-world conditions. Even the best-performing tool failed in almost 15% of cases, with others performing worse. None of tested applications consistently provided a single, correct answer, demonstrating they cannot be trusted for definitive life-or-death identification decisions.

Keywords:

food safety, toxicity, mushroom foraging, sustainability, artificial intelligence (AI), AI application, species identification, fungi, Macromycetes

Science fiction often portrays apocalyptic scenarios in which computers rebel against humanity, culminating in the rise of a militant AI and eventual destruction of civilization. While these scenarios remain firmly in the realm of fiction, it is worth noting that even imperfect AI systems, prone to errors, can pose risks comparable to those of rogue or malicious AI.

The rapid proliferation of AI technologies across nearly every domain of human cultural and daily life, while yielding significant advancements, also introduces notable risks [1-3]. These risks are particularly pronounced when the users place unwarranted trusts in AI as a reliable source of information or disregard warnings about its possible inaccuracies. A clear example of this trend is the proliferation of apps that claim to provide "guaranteed" identification of natural objects.

Modern automated tools increasingly employ AI, primarily through deep learning techniques such as Convolutional Neural Networks (CNNs). The integration of computer vision and machine learning methods within the mushroom industry is summarised in [4]. In essence, these systems are trained on vast datasets of labeled images, where they automatically learn to recognize hierarchical visual patterns—from basic edges and textures to complex, species-specific shapes—by repeatedly adjusting internal parameters to minimize identification errors.

In practical application, the AI identification process for a user-submitted photograph follows a standardised computational pipeline (Figure 1). The system begins by extracting visual features from the input image. It then compares these features against its learned model, ultimately generating a classification by assigning probability scores to different species. The final output is typically a ranked list of suggested identifications. Understanding this workflow is key to appreciating the potential sources of error in AI-based identification, which can arise from limitations in training data, algorithmic biases, or challenges in processing complex real-world images that deviate from idealized examples.

Broadly, users of these AI applications in natural settings can be categorized into three groups, each facing varying levels of risk when making crucial decisions influenced by AI-generated guidance. Recreational activities, such as exploring wildlife and identifying plants or fungi during forest walks, generally pose minimal risks. Mushroom foraging, has deep roots in cultural traditions and generates scientific interest in fungal communities and their ecological interactions [5-9].

A fundamental limitation of AI-based identification is its exclusive dependence on visual data from photographs. This contrasts with the holistic approach of traditional mycological expertise, where confident foraging relies on integrating non-visual sensory cues (e.g., smell and texture) and key ecological parameters (e.g., substrate, seasonality, and regional context). This nuanced, context-dependent knowledge is not captured in photographs and is therefore absent from the training of global AI models. The broader cultural and contextual complexities involved in distinguishing edible from toxic species have been explored in prior work [10,11].

When AI applications are used for scientific purposes requiring precise species identification, AI errors can lead to inaccuracies that may compromise research outcomes. The risks become more consequential when mushrooms are identified for collection and consumption. Mistaken identification and decisions regarding edibility can result in illness or, in severe cases, have fatal outcomes. Regrettably, AI-mediated errors in mushroom identification have already been documented, with an increasing number of incidents reported [12,13], Supplementary Note 1. As the old Irish adage wisely warns: “There are old mushroom hunters and there are bold mushroom hunters. But there are no old bold mushroom hunters.”

Below, we outline the top ten primary complications and causative factors contributing to the malfunctions of AI applications. Additionally, evaluation of the twelve Fungi Identification AI-based Resources (FIARs) — six software programs and six mobile applications — was performed using a four-point scoring scale (see Methods). An overall score was then calculated to assess the general accuracy and practical utility of each application.

1. Occlusion

Occlusion is a fundamental challenge in computer vision that arises when an object is partially obscured by another object or its context. For example, a vivid red-capped scaber stalk (*Leccinum aurantiacum)* occluded by lingonberry shrubs in the first image (Figure 2 – Photo #1) was not correctly identified by any of 12 applications tested (Figure 3; Supplementary Data 2). Яндекс (Yandex), for instance, recognized only the lingonberry leaves, while several other AI tools misidentified the object. Copilot suggested *Boletus reticulatus,* Champignouf identified *Psathyrella candolleana*, and Danish software Svampe purposed the term "Dear wax hat," whose meaning remains unclear. The Google Lens application missed the mushroom entirely, focusing instead on the red spots of lingonberry leaves in the foreground. Consequently, it identified the species as *Exobasidium rhododendri*, a basidiomycete closely related to the redleaf fungus (*Exobasidium vaccinii)*, which causes galls on lingonberry leaves [14].

The partially occluded mushrooms (Figure 2 – Photos #2, 3, 4, and 5) were recognized by a total of five, eight, six, and seven different applications, respectively (Figure 3). However, only a few of these applications correctly identified the species. In contrast, 9 out of the 12 applications successfully recognized and correctly identified the species of the non-occluded mushroom (Figure 2 – Photo #6; Figure 3). Even minor occlusion caused by contextual elements contributed to the misidentification of several other fungal genera and species by many of the AI applications (Figure 2 – Photos #28 -30; Figure 3).

In the Occlusion test (Figure 2 – Photos ##1 - 6; Figure 3), Picture Mushroom performed best, achieving the score of 10 points. iNaturalist, Atlas of Danish Fungi, and Svampe followed, each scoring 7 points. At the lowest performance level, Copilot, Seek by iNaturalist, and imagerecognize.com scored 0 points, as none provided correct answers across the test. This reveals a critical reliability divide: some tools manage partial occlusion better, while others fail entirely, limiting their utility in common real-world conditions.

2. Camouflage of Mushrooms

Many northern fungal species produce fruit bodies during autumn that exhibit dull, earth-toned coloration, blending into the surrounding forest [15,16]. The cryptic appearance, or crypsis, likely provides protection by reducing the likelihood of detection by animals prior to spore dispersal [17,18]. While mimicry in fungi remains a debated topic due to limited empirical evidence [15,19,20], some species exhibit highly effective camouflage that can confuse both humans and AI systems.

A notable example is the yellowfoot or winter chanterelle *(Craterellus tubaeformis)*, whose fruiting bodies are difficult to detect in the deciduous forests, even for experienced mushroom foragers. Unsurprisingly, many AI applications fail to identify this species in natural settings (Figure 2 – Photos #7-9). Remarkably, some AI tools, including Copilot, did not recognize it even after it had been cleaned and placed in a domestic setting, such as on a kitchen counter (Figure 2 – Photo #10). Picture Mushroom and iNaturalist were the only FIARs that avoided incorrect identifications In the Camouflage test (Figure 2 – Photos ##7 - 10; Figure 3).

3. Influence of Lighting, Contrast, and Background

In image-based object recognition, contrast and background are critical variables—and fungal identification by AI tools is no exception. In general, higher image contrast is associated with improved recognition accuracy. For example, a photo of *Boletus edulis* taken at night with flash against a dark background (Figure 2 – Photo #12) produced better AI recognition results than a similar image taken during the day under diffuse light with a green moss background (Figure 2 – Photo #11), or one photographed under artificial lighting on a colored newspaper (Figure 2 – Photo #13). The influence of complex backgrounds was particularly evident when even the best-performing tools, Picture Mushroom and iNaturalist, failed to identify *Boletus edulis* under artificial lighting against a colored newspaper background (Figure 2 – Photo #13; Figure 3). These findings underscore the importance of lighting conditions, image contrast, and background uniformity in AI-mediated species identification.

Similar trends were observed with other fungal species. *Pholiota squarrosa*, was recognized by 7 out of 12 applications when shown in a high-contrast image with a natural background (Figure 2 – Photo #14), compared to only 3 out of 12 applications when photographed under artificial lighting with a colored, non-natural background (Figure 2 – Photo #15). This further illustrates the importance of background context and lighting quality in AI-mediated identification.

4. Processed Mushrooms

As anticipated, photographs of collected and processed mushrooms proved more difficult for AI systems to identify accurately. A previous study using real-world images submitted by the public in Australia reported similar findings [21]. Photos of mushrooms prepared for cooking often featured incomplete specimens, suboptimal lighting, and non-standardized backgrounds, all of which negatively impacted recognition performance.

Similar misidentification issues were observed for several commonly foraged European species when presented in processed form. Notable examples include images of *Boletus edulis* (Figure 2 – Photo #13), *Pholiota squarrosa* (Figure 2 – Photo #15 vs. Photo #14), *Albatrellus ovinus* (Figure 2 – Photos #16, #17) at different preparation conditions. Among processed specimens the performance varied significantly. While three FIARs (Picture Mushroom, Champignouf, Svampe) provided tentative identifications for processed Pholiota squarrosa in a kitchen setting still with other options listed, none succeeded with cleaned Albatrellus ovinus. For the latter, only Google Lens, iNaturalist, and Yandex (Яндекс) listed the correct species among several other suggestions (Figure 2 – Photos ##14 - 17; Figure 3).

These cases highlight how the physical alteration of specimens can obscure key morphological features necessary for accurate AI-based identification.

5. Mushroom Morphology Variation

Basidiomycetes are known for their considerable intraspecific morphological variation [22,23]. Most AI applications, predictably, are trained and biased toward recognizing fungi with "standard" or typical appearances. The variation of fungi fruiting bodies poses a considerable challenge for accurate identification. For instance, a group of three fruiting bodies of *Paxillus* *involutus* exhibiting atypical morphology (Figure 2 – Photos #18, #19), markedly different from the classic form (Figure 2 – Photo #20), were not recognized by 6 to 8 of the tested applications.

Particularly, six FIARs (Picture Mushroom, Champignouf, Mushroom Identificator, iNaturalist, Google Lens, and Yandex) included the correct *P. involutus* in a list of tentative suggestions, though inconsistently (Mushroom Identificator and Yandex identified only 1 of 2 images). Two tools (Atlas of Danish Fungi and Svampe) failed entirely on both test images.

Moreover, morphological differences between the earlier stages and its mature fruiting bodies can substantially reduce the accuracy and reliability of AI-based identification. A well know example is the toxic fly agaric (*Amanita muscaria*), whose "button" stage appears distinctively different from its mature form [24]. This disparity often leads to misidentification, particularly among inexperienced mushroom foragers. While it may be expected that AI systems could resolve such challenges, current tools consistently fail to identify early-stage specimens with acceptable accuracy.

Particular caution is warranted when using AI tools to identify immature mushrooms. Imaging of fruiting bodies at early developmental stages presents substantial challenges for species recognition. In this study, only 3 of the 12 tested applications (Picture Mushroom, Champignouf, and imagerecognize.com) listed *Amanita muscaria* when presented in its immature "button" stage (Figure 2 – Photo #25), compared to 10 of 12 applications that correctly identified the species in its mature form (Figure 2 – Photos #24, #26).

6. Imaging of Multiple Species in a Single Photo

The presence of multiple fungal species within the same image complicates the identification process, as many AI tools appear to be designed to recognize only a single species per photograph. For instance, when *Paxillus involutus* appeared alone (Figure 2 – Photo #20), the Chinese application 鸡油菌 accurately identified it. However, the same application failed to recognize *P. involutus* when it was pictured alongside *Lactarius turpis* (Figure 2 – Photos #21, #22, #23), highlighting the limitations of multi-species recognition in current AI systems.

Camera angle also influenced the ability of AI tools to accurately identify multiple species within a single image. Notably, Яндекс (Yandex) performed better when the fungi were photographed from an elevated angle (Figure 2 – Photo #21), while iNaturalist produced more accurate results from a lower and direct top-down presentation (Figure 2 – Photos #22, #23). Picture Mushroom, Mushroom Identificator, Atlas of Danish Fungi, and Svampe demonstrated consistent identification performance across different camera angles.

7. Similarity of Interspecific Coloration

Visual similarity in coloration and surface patterns across different fungi species present significant challenges for AI-based identification. For instance, the orange-colored cap of *Leccinum aurantiacum* with white specks (Figure 2 – Photo #27) was incorrectly classified by Copilot as *Omphalotus olearius* (Jack-O'Lantern), *Mycena leaiana* (orange mycena), or *Amanita muscaria var. guessowii* (orange fly agaric).

In another case, Russula sp. (Figure 2 – Photo #29) was misidentified by Champignouf application as *Baorangia bicolor, Leratiomyces ceres, Imperator sp., Boletus edulis,* or *Amanita muscaria*. One AI tool (imagerecognize.com) even misclassified the specimen as an apple, with confidence of 99 %.

Compounding the issue, environmental factors can alter key features. For example, the white scales typical of mature *Amanita muscaria* can be washed off in wet weather conditions (Figure 2 – Photo #24), increasing the risk of confusion with red *Russula* species. Similarly, *Leccinum scabrum* (birch bolete) was misidentified by Copilot and Google Lens as *Boletus edulis*, and further confused with *Suillus granulatus* (weeping bolete) by Яндекс (Yandex) and Champignouf, particularly when the photograph was taken in damp conditions (Figure 2 – Photo #30).

8. Species Diversity in Basidiomycetes

In addition to morphological variability, the vast taxonomic diversity within the Division Basidiomycota presents a substantial challenge for accurate species identification. Even among experts, classification remains unsettled for many taxa. A significant portion of the time at mycological conferences, including the recent International Mycological Congress (IMC12, 2024), is often devoted to resolving the systematic positions and updating nomenclature.

A striking example is the former classification of the genus *Armillaria*, which historically served as a “wastebasket” taxon encompassing over 270 species of agaric mushrooms with similar macroscopic traits, such as stem-attached gills, a ring, and a white spore print. Following taxonomic revision in 1995, only about 40 species remained within *Armillaria*, while the others were reassigned to 43 separate genera [25].

Many fungal species cannot be reliably identified by appearance alone, requiring DNA sequencing and phylogenetic analysis for accurate classification. This poses a limitation for AI tools, which typically rely on visual data. Furthermore, species with limited culinary, ecological, or medicinal relevance are often underrepresented in training datasets, resulting in poor recognition by AI applications biased toward commonly known edible or toxic fungi (Figure 2 – Photos #31 - #40; Figure 3).

9. *Mislabeling and Misinformation*

Accurate labeling is critical for the reliability of AI systems, particularly in tasks involving species identification. Mislabeling by non-specialists, such as photo authors or content uploaders, can introduce noise into datasets and misguide the training and performance of AI models.

A common example involves images of wood-decaying fungi such as *Fomes fomentarius*, *Phellinus igniarius*, and *Fomitopsis pinicola*, which are frequently mislabeled online as “chaga” (чага). However, true chaga refers specifically to the sclerotium of *Inonotus obliquus*, a distinct species used in folk medicine and subject to ongoing taxonomic and pharmacological debate [26–30].

Additionally, AI systems themselves contribute to the issue by arbitrarily assigning incorrect species names to images, sometimes even generating fictitious mushrooms and labeling them with legitimate scientific names [31,32]. Such errors degrade the overall accuracy and trustworthiness of AI-generated identifications.

10. Geographical and Temporal Biases

Although many modern AI platforms are globally accessible, their performance often reflects the geographical origin and temporal scope of their training datasets. As a result, certain tools exhibit regional biases that limit their effectiveness outside of their primary cultural or ecological context.

For example, the yellowfoot or winter chanterelle (*Craterellus tubaeformis*), known as Trattkantarell in Scandinavia, is a common and widely foraged mushroom in Northern Europe. However, it was not recognized by regionally developed platforms such as Яндекс (Yandex) (Russia) and **菌窝子** (China). Similarly, species widely consumed in Western countries, *Boletus edulis* (porcino), *Leccinum scabrum* (birch bolete), *Suillus granulatus* (weeping bolete) were not identified by 菌窝子. Conversely, mushrooms familiar in Eastern markets, such as termite mushroom, 鸡枞菌 (*Termitomyces yunnanensis*) [33], flat chanterelle, 鸡油菌 (*Cantharellus applanatus*) [34], and rugiboletus, 皱牛肝菌 (*Rugiboletus extremiorientalis*) [35], were not reliably recognized by AI applications primarily developed for Western use.

Among the tested platforms, the Chinese application 菌窝子 demonstrated superior performance with Eastern species (Supplementary Figure 1), but even this app failed to identify some novel fungi. For example, matijun (**馬蹄均**, *Turbinellus matijun*, *Gomphus matijun*), a recently introduced edible mushroom in Asian markets [36], was not recognized by any of the 12 tested AI platforms. This highlights the limitations of static training datasets and the need for regular updates to accommodate emerging species.

Performance Analysis of Fungi Identification AI-based Resources (FIARs)

The comparative analysis using the Total Rating Score (TRS), a cumulative metric derived from the sum of scores across all tests, revealed significant disparities in the real-world functionality of the evaluated FIARs. The mobile app Picture Mushroom was the top performer (TRS: 171), indicating superior general reliability. However, even this best-performing tool failed to provide a correct identification in nearly 15% of test cases.

A tight cluster of four subsequent tools performed with similar overall proficiency (TRS: 145–147) but exhibited varied strengths across different test types. This group comprised the app Atlas of Danish Fungi (147) and three PC-based resources: Champignouf (146), Google Lens (146), and Svampe (145). The average error rate for these four FIARs was approximately 20 ± 2%.

The next tier, representing moderate performance, included four FIARs with lower TRS values: the apps iNaturalist (127), Mushroom Identificator (120), 菌窝子 (94), and the search engine Yandex (112). This group had an average error rate of nearly 40%. Notably, 菌窝子 demonstrated a unique strength, providing a single, unambiguous correct answer in over 18% of tests—a rate almost triple that of the top-ranked Picture Mushroom, which did so in only 6.8% of cases.

The lowest-performing group included two AI tools with surprisingly poor results given their popularity or specialization: Copilot and the dedicated app Seek by iNaturalist, each scoring 51 points. The software imagerecognize.com was the worst overall performer (16 points), providing incorrect answers in over 90% of tests. The average error rate for these three FIARs exceeded 80%, equating to more than four wrong answers for every five tests conducted.

Bridging the Gap to Next-Generation Identification

Ultimately, the problem of accurate species identification in mushroom foraging and applied mycology is no less critical than forensic suspect identification, as both fields fundamentally concern public health and safety. It is therefore difficult to justify tolerating identification tools with error probabilities of 15-40% - a standard no detective agency would accept.

This stark reality underscores the significant gap between the precision of modern laboratory technology - utilizing instrumental methods such as chromatography, mass spectrometry, spectroscopy, and molecular biology - and the situation of a forager in the field. When confronting the vast diversity of fungi in nature, one must still rely primarily on personal senses—vision, olfaction, and touch—coupled with individual knowledge and experience. This task is further complicated by inherent biological challenges like phenotypic plasticity and homoplasy in Macromycetes [37-39]. Consequently, there remains a significant, unmet need among both mushroom foragers and field mycologists for reliable, portable identification tools.

Addressing this gap requires the development of wearable, miniaturized chemosensors. Integrating lab-on-chip (LoC) platforms, electronic nose (E-nose), and electronic tongue (E-tongue) technologies into such devices would allow for on-site biochemical profiling, including the critical detection and quantification of mycotoxins [40-43]. Such innovations should complement the ongoing refinement of AI-based computer vision identification systems. Another promising avenue lies in the development of field-deployable biosensors and smart molecular biology analyzers capable of detecting specific biomarker genes via rapid PCR techniques or portable next-generation sequencing (NGS) [44-46].

In conclusion, identifying mushrooms based solely on visual appearance is inherently challenging, even for trained experts. While AI-powered platforms continue to grow in popularity, their effectiveness in real-world scenarios remains limited. All of the applications evaluated in this study showed only conditional accuracy and reliability and failed to identify several fungi images, each demonstrating some degree of limitation. As such, users should exercise caution when relying on these tools, particularly when identification carries potential health or food safety risks. Correct fungal identification via AI is not guaranteed. While the accuracy and reliability of an AI identification are the responsibility of its developers, the final decision to trust and utilize that identification for consumption remains the sole responsibility of the user.

The use of AI in natural object identification, such as fungal species, represents only a small example of the broader concerns tied to artificial intelligence. Many risks—both current and future—are poorly defined and often underestimated. As human–AI interaction becomes increasingly ubiquitous, it is important to question not only the capabilities of AI, but also the assumptions we make about our role in guiding its use.

Methods

Image Dataset Acquisition

All digital photographs of Macromycetes fruiting bodies were taken and collected by the authors over a 15-year period from 2009 to 2024. Specimens were photographed in their natural ecological contexts across diverse forested regions of Eurasia, as well as specimens obtained from local markets to ensure a representative sample of morphological and taxonomical variability. From this curated collection, 103 high-quality digital photographs were selected for the study, representing 62 species across 40 genera (see Supplementary Data 3: Original mushroom photographs M01-M48).

Taxonomic Verification

Specimen identification followed a rigorous, region-specific protocol. European species were identified using established field identification handbooks in conjunction with the research team's extensive foraging experience. Asian species were verified in collaboration with a dedicated mycology expert possessing over 25 years of taxonomic expertise in the region.

Photographic Equipment and Settings

To ensure consistency and durability in varied field conditions, all images were captured using all-weather, shock-resistant compact digital cameras. A Pentax Optio W80 was used from 2009 to 2013, and a Pentax Optio WG-2 was used from 2014 to 2024. All photographs were taken at the maximum native resolution of each camera: 12 megapixels (MP) for the Optio W80 and 16 MP for the Optio WG-2. The macro focus mode was employed in the vast majority of cases to capture fine morphological details. The built-in camera flash was utilized only under low-light conditions (e.g., evenings, dense forest canopy).

Image Curation and Test Group Design

All original images were saved by the cameras in JPEG format, transferred, and archived on a dedicated external hard drive. Crucially, none of these photographs were published online prior to this study, ensuring the entire image corpus was novel to all AI systems at the time of testing.

For systematic analysis, 48 representative images were organized into nine thematic Topic Test Groups **(**TTGs**).** This structure allowed for the evaluation of AI performance across different visual and taxonomic challenges (Figure 2, Supplementary Figure 1).

Selection of Fungi Identification AI-based Resources (FIARs)

An initial screening of over 30 publicly available applications and websites was conducted based on user ratings from the Apple App Store, Google Play Store, and Google search results. From this pool, twelve FIARs were selected for comparative analysis, comprising six mobile applications and six web-based platforms. The selection aimed to represent a range of widely available and user-rated tools for practical, real-world evaluation (see Figure 3 and Supplementary Data 2).

AI Query Protocol and Testing Procedure

Device and Researcher Setup: Three researchers independently tested the 12 selected FIARs. Each researcher reviewed the full list of AI-generated responses for every query, recorded whether the correct identification was present, and noted its rank in the suggestion list. Testing was conducted on personal devices to simulate real-user conditions:

- **Researcher 1**: Samsung Galaxy Tab S8 (Samsung Electronics, 2022) and an ASUS Vivobook 16X M1603 notebook PC (Windows 11).
- **Researcher 2**: iPhone 13 (Apple Inc., 2021).
- **Researcher 3**: Motorola G54 smartphone (Motorola Mobility, 2023).

Image Presentation: All images were presented to the AI tools using a Query by Image Content (QBIC) approach. To replicate a realistic user scenario, each original, unmodified image file was uploaded directly to the application or web interface. Photographs containing single or multiple specimens were not cropped or segmented; the AI was presented with the complete scene as captured.

Response Evaluation and Scoring: Validation of outputs was performed using the verified Latin binomial species names as well as common names in four languages: English, Swedish, Russian, and Chinese (Supplementary Table 1).

The accuracy of each AI-generated response was evaluated using a four-point scoring scale (0–3), applied independently by the three researchers:

0: Only incorrect answers were listed.

1: The correct answer was included, but not ranked first.

2: The correct answer was ranked as the first suggestion.

3: Only the single correct answer was provided.

Data Analysis and Scenario-Based Performance Evaluation

Overall Performance Metric: To assess the general reliability of each FIAR, a Total Rating Score (TRS) was calculated by summing its scores across all ten tests using Microsoft Excel. This cumulative metric provides a comparative overview of utility across all 12 tested AI-based tools.

Detailed Performance Breakdown: To identify specific strengths, weaknesses, and failure modes, localized scores were compiled for each FIAR within each Topic Test Group (TTG). These scores, visualized in the Supplementary Data 2 and in the Excel tables embedded in Figure 3 and Supplementary Figure 1, reflect performance across predefined major complication categories:

1. ***Occlusion:*** Objects partially obscuring the mushroom.
2. ***Camouflage of Mushrooms:*** Specimens are lost against the general background.
3. ***Influence of lighting, contrast, and background:*** Challenging photographic conditions.
4. ***Processed mushrooms:*** Collected, cleaned, or cut specimens.
5. ***Mushroom morphology variation:*** Intra-species shape or developmental differences.
6. ***Multiple species per image:*** Photographs containing two or more distinct species.
7. ***Interspecific coloration similarity:*** Different species with highly similar color patterns.
8. ***Basidiomycete species diversity:*** Tests across a wide taxonomic spread.
9. ***Mislabeling and misinformation:*** Incorrect common name prompts.
10. ***Geographical and temporal biases:*** Species outside a tool's presumed training data.

Data availability: All data has been included in this article and the supplemental material section.

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Figures

Figure 1

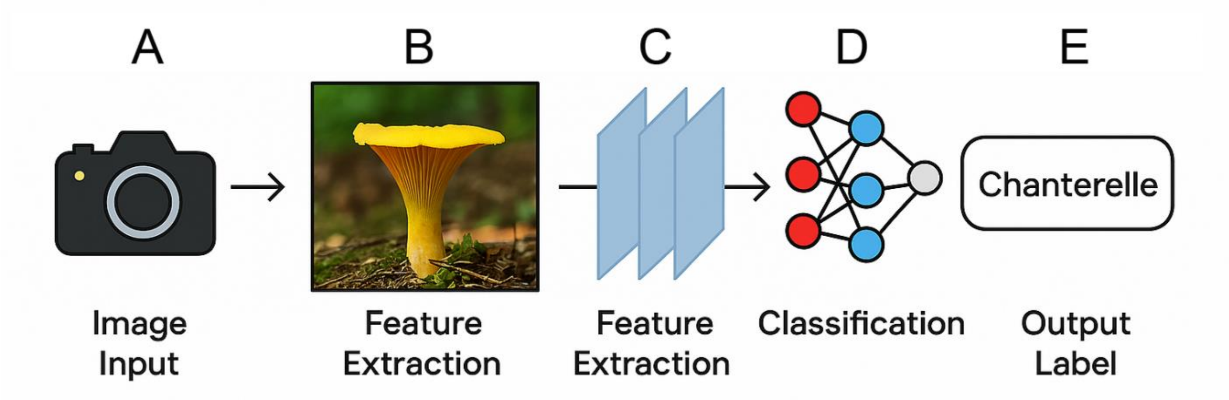

Figure 2


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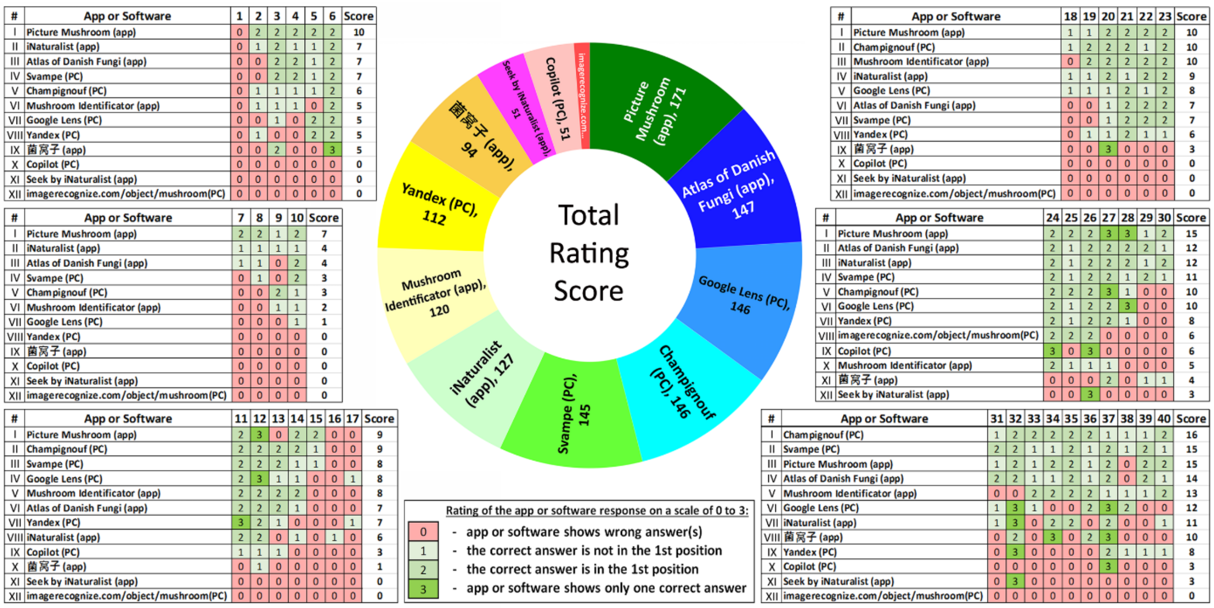
Figure 3



#	App or Software	1	2	3	4	5	6	Score
I	Picture Mushroom (app)	0	2	2	2	2	2	10
II	iNaturalist (app)	0	1	2	1	1	2	7
III	Atlas of Danish Fungi (app)	0	0	2	2	1	2	7
IV	Svampe (PC)	0	0	2	2	1	2	7
V	Champignouf (PC)	0	1	1	1	1	2	6
VI	Mushroom Identificator (app)	0	1	1	1	0	2	5
VII	Google Lens (PC)	0	0	1	0	2	2	5
VIII	Yandex (PC)	0	1	0	0	2	2	5
IX	菌窝子 (app)	0	0	2	0	0	3	5
X	Copilot (PC)	0	0	0	0	0	0	0
XI	Seek by iNaturalist (app)	0	0	0	0	0	0	0
XII	imagerecognize.com/object/mushroom(PC)	0	0	0	0	0	0	0

#	App or Software	7	8	9	10	Score
I	Picture Mushroom (app)	2	2	1	2	7
II	iNaturalist (app)	1	1	1	1	4
III	Atlas of Danish Fungi (app)	1	1	0	2	4
IV	Svampe (PC)	0	1	0	2	3
V	Champignouf (PC)	0	0	2	1	3
VI	Mushroom Identificator (app)	0	0	1	1	2
VII	Google Lens (PC)	0	0	0	1	1
VIII	Yandex (PC)	0	0	0	0	0
IX	菌窝子 (app)	0	0	0	0	0
X	Copilot (PC)	0	0	0	0	0
XI	Seek by iNaturalist (app)	0	0	0	0	0
XII	imagerecognize.com/object/mushroom(PC)	0	0	0	0	0

#	App or Software	11	12	13	14	15	16	17	Score
I	Picture Mushroom (app)	2	3	0	2	2	0	0	9
II	Champignouf (PC)	2	2	2	2	1	0	0	9
III	Svampe (PC)	2	2	2	1	1	0	0	8
IV	Google Lens (PC)	2	3	1	1	0	0	1	8
V	Mushroom Identificator (app)	2	2	2	2	0	0	0	8
VI	Atlas of Danish Fungi (app)	2	2	2	1	0	0	0	7
VII	Yandex (PC)	3	2	1	0	0	0	1	7
VIII	iNaturalist (app)	2	2	0	1	0	1	0	6
IX	Copilot (PC)	1	1	1	0	0	0	0	3
X	菌窝子 (app)	0	1	0	0	0	0	0	1
XI	Seek by iNaturalist (app)	0	0	0	0	0	0	0	0
XII	imagerecognize.com/object/mushroom(PC)	0	0	0	0	0	0	0	0

#	App or Software	18	19	20	21	22	23	Score
I	Picture Mushroom (app)	1	1	2	2	2	2	10
II	Champignouf (PC)	1	2	2	2	1	2	10
III	Mushroom Identificator (app)	0	2	2	2	2	2	10
IV	iNaturalist (app)	1	1	2	1	2	2	9
V	Google Lens (PC)	1	1	1	2	1	2	8
VI	Atlas of Danish Fungi (app)	0	0	1	2	2	2	7
VII	Svampe (PC)	0	0	1	2	2	2	7
VIII	Yandex (PC)	0	1	1	2	1	1	6
IX	菌窝子 (app)	0	0	3	0	0	0	3
X	Copilot (PC)	0	0	0	0	0	0	0
XI	Seek by iNaturalist (app)	0	0	0	0	0	0	0
XII	imagerecognize.com/object/mushroom(PC)	0	0	0	0	0	0	0

#	App or Software	24	25	26	27	28	29	30	Score
I	Picture Mushroom (app)	2	2	2	3	3	1	2	15
II	Atlas of Danish Fungi (app)	2	1	2	2	2	2	1	12
III	iNaturalist (app)	2	1	2	2	2	1	2	12
IV	Svampe (PC)	2	1	2	2	1	2	1	11
V	Champignouf (PC)	2	2	2	3	1	0	0	10
VI	Google Lens (PC)	2	1	2	2	3	0	0	10
VII	Yandex (PC)	2	1	2	2	1	0	0	8
VIII	imagerecognize.com/object/mushroom(PC)	2	2	2	0	0	0	0	6
IX	Copilot (PC)	3	0	3	0	0	0	0	6
X	Mushroom Identificator (app)	2	1	1	1	0	0	0	5
XI	菌窝子 (app)	0	0	0	2	0	1	1	4
XII	Seek by iNaturalist (app)	0	0	3	0	0	0	0	3

#	App or Software	31	32	33	34	35	36	37	38	39	40	Score
I	Champignouf (PC)	1	2	2	2	2	2	1	1	1	2	16
II	Svampe (PC)	2	2	1	1	2	1	2	1	2	1	15
III	Picture Mushroom (app)	1	2	1	2	2	1	2	0	2	2	15
IV	Atlas of Danish Fungi (app)	2	2	1	1	2	1	2	0	2	1	14
V	Mushroom Identificator (app)	0	0	2	2	2	2	1	1	1	2	13
VI	Google Lens (PC)	1	3	1	0	0	2	3	2	0	0	12
VII	iNaturalist (app)	1	3	0	2	2	0	2	0	0	1	11
VIII	菌窝子 (app)	0	2	0	3	0	2	3	0	0	0	10
IX	Yandex (PC)	0	3	0	0	0	0	2	1	1	1	8
X	Copilot (PC)	0	0	0	0	0	0	3	0	0	0	3
XI	Seek by iNaturalist (app)	0	3	0	0	0	0	0	0	0	0	3
XII	imagerecognize.com/object/mushroom(PC)	0	0	0	0	0	0	0	0	0	0	0

Figure Legends

Figure 1. Schematic of an AI-based mushroom identification pipeline.

A. Image Input: A user submits a digital photograph of a mushroom. An image is converted into pixel data for conversion. **B. Feature Extraction:** A Convolutional Neural Network (CNN) processes the pixel data to extract hierarchical visual features, progressing from low-level edges and textures to high-level morphological patterns. **C. Feature Extraction:** The extracted features are passed through fully connected layers or other classifiers to assign probabilities to mushroom spaces. **D. Classification:** The extracted features are analyzed against a trained knowledge base to generate ranked set of probabilistic species predictions. **E. Output Label:** The system presents the most likely class (e.g., "Chanterelle") as the final identification result to the user.

Figure 2. Data curation and Topic Test Groups (TTGs).

The dataset was compiled from 103 original photographs of Macromycetes fruiting bodies (representing 62 species across 40 genera) taken by the authors. For systematic analysis, 40 representative images shown were grouped into thematic TTGs. (The experimental settings for subsequent test are detailed in the Supplementary Figure 1.)

Figure 3. Comparative performance of twelve Fungi Identification AI-based Resources (FIARs) on real-world mushroom images.

The accuracy of each AI-generated response was evaluated using a four-point scoring scale (0–3): **0:** Only incorrect answers were listed; **1:** The correct answer was included, but not ranked first; **2:** The correct answer was ranked as the first suggestion; **3:** Only the single correct answer was provided. The tables within the figure were created in Microsoft Excel. Numbers in the Table column headings correspond to the photographs numbers in Figure 2. The central chart illustrates the comparative Total Rating Score (TRS) results for each FIAR—a cumulative metric of general accuracy and practical utility derived from the sum of its scores across all tests (see text for details).

Supplementary files:

Supplementary Data 1:

- **Supplementary Note 1. Confirmed Case Reports & Incidents**
- **Supplementary Figure 1. Asian markets fungi species were poorly identified by Western FIARs**

Mushrooms, beloved in East, present a challenge to the versatility of AI-based applications intended primarily for Western use. Mushrooms from Asian markets are more effectively recognized by the Chinese app. The table within the figure was created in Microsoft Excel.

- **Supplementary Table 1: Key Reference Table - Mushroom picture numbers and Names**

Supplementary Data 2: Mushroom Identification software and apps output Evaluation

Supplementary Data 3: Original mushroom photographs M01-M48