Cureus Journal of Computer Science

Open Access Original Article

Mush-Room for Innovation: Internet of Things, Machine Learning, and Generative Pre-Trained Transformers Integration

Received 02/26/2025
Review began 02/28/2025
Review ended 06/03/2025
Published 06/13/2025

DOI: https://doi.org/10.7759/s44389-025-03223-1

Samer T. Abaddi [1]

1. Research Department, IDentity Research, Amman, JOR

Corresponding author: Samer T. Abaddi, eng.sameralabbadi@gmail.com

Abstract

Mushroom farming is a vital sector in Jordan's agriculture (set to reach 1,060 metric tons by 2026). This study aims to revolutionize mushroom farming through the integration of the Internet of Things (IoT) and artificial intelligence (AI) capabilities through machine learning and the generative pre-trained transformer-4omni (GPT-4o) most recent model. A comprehensive hardware and software architecture was developed after training three machine vision models (Visual Geometry Group 16 - VGG16, Inception Third Version - InceptionV3, and Residual Network - ResNet50) and integrating GPT-4o for sound and text recommendations and an interactive dashboard with the alarming system. A robust dataset of (n = 4,755) images was meticulously processed, achieving the highest classification accuracy of 91.5% with ResNet50. The system's static and real-time vision capabilities were validated with a prototype, integrating sensors for temperature, humidity, and gas levels. Unlike previous studies, this research uniquely combines IoT and AI with GPT-4o, providing intelligent recommendations and visual dashboards. The results demonstrated significant improvements, with practical applications extending to open-source tools for global use. Future research could explore drone integration and address privacy and security concerns. This study sets a new standard in agricultural technology, offering a scalable, efficient solution for modern mushroom farming and the potential to extend to further applications.

Categories: AI applications, Computer Vision, Machine Learning (ML)
Keywords: mushroom farming, internet of things, artificial intelligence, generative pre-trained transformer 4 omni in agriculture, agriculture technology, machine vision

Introduction

The advent of the Fourth Industrial Revolution has ushered in a new era of technological advancements characterized by the fusion of physical, digital, and biological systems. Examples of such advancement are the Internet of Things (IoT), machine learning (ML), and generative pre-trained transformers (GPTs), enabling unprecedented levels of automation and efficiency [1-2]. Both, GPT and ML are part of the artificial intelligence (AI) family.

Jordan contends with a challenging agricultural environment that has historically shaped its culture and economy. The nation faces critical issues such as water scarcity and climate change, necessitating innovative agricultural practices to ensure sustainability [3]. Leveraging advanced technologies presents a transformative opportunity for enhancing agricultural productivity, particularly in mushroom farming. IoT and AI technologies have been instrumental globally in monitoring environmental conditions and improving crop quality [4]. The global market for AI in agriculture was valued at 1.7 billion U.S. dollars in the year 2023 [5]. The IoT market is expected to clock 7 billion U.S. dollars by 2025 [6].

Mushroom farming is a laborious process that warrants a close watch over the environment for optimum yields. Conventional mushroom farming techniques are pretty labor-intensive and are also at the risk of human error, resulting in varying yields and quality. IoT in mushroom farming incorporates perfect sensor technology to offer real-time monitoring and control of such critical factors as humidity, temperature, and light intensity [7]. This capability is particularly beneficial for regions like Jordan (the second most water-scarce country in the world), where climatic fluctuations can significantly impact agricultural processes [8]. Real-time data collection enabled by IoT provides farmers with essential insights, facilitating optimal crop management and resource utilization. ML further enhances this process by analyzing historical data to predict optimal harvesting times, thereby increasing efficiency and reducing resource wastage. The ML algorithms offer a high-level classification to categorize mushrooms into two classes, namely, "poisonous" and "edible", which enhances safety and decreases likelihood factor [7]. Furthermore, one successful trial integrating the GPT-4 deep logical reasoning and You Only Look Once network visual capabilities proved that both technologies are loaded with potential to elevate itself upwards of 90% in terms of pathology diagnosis for agriculture [9].

The agricultural sector in Jordan is under massive pressure, facing great challenges which limit its productivity and sustainability. The top pressing challenges include water scarcity, uncertainty of climate conditions, and unavailability of arable lands [10]. According to the International Trade Administration, Jordan's agriculture absorbs around half of the water resources and makes less than 5.9% of the gross domestic product [11], highlighting an urgent need for more efficient resource management. Moreover, the traditional farming practices currently in use are insufficient to meet the increasing demand for food due to population growth and changing dietary preferences.

Mushroom farming, despite its potential as a high-yield, nutrient-rich agricultural product, is particularly vulnerable to these environmental and resource-related constraints. Traditional methods of cultivating mushrooms are laborious inefficient and may result in poor yields with the subsequent increased biomaterial loss. Rehman et al. stated that the reliance on manual monitoring and control of environmental conditions such as temperature and humidity exposes the crops to greater risks of disease and inconsistent growth [7]. Moreover, the mushroom farming industry is facing increasing pressure to improve efficiency and reduce environmental impact. High operational costs result because they are resource intensive in not just labor but other aspects too, including the environmental degradation resulting from specific methods being adopted for long periods [12]. So, the integration of IoT, ML, and GPT offers a promising solution to those challenges. IoT systems enable real-time monitoring and precise control of the farming environment, and ML algorithms can analyze vast amounts of data to predict optimal growing conditions and classify edibles from poisonous or expired. However, the implementation of these advanced technologies into the agricultural practices of Jordan, like those in other developing countries in the Middle East and North Africa region, remains low, especially in mushroom farming, due to high initial costs, lack of technical expertise, and resistance to change among traditional farmers [13].

The primary objective of this study is to develop an automated system that integrates IoT and AI technologies to enhance the efficiency, productivity, and sustainability of mushroom farming in Jordan. This overarching goal encompasses several specific objectives:

• Develop a comprehensive hardware and software architecture for the proposed system, ensuring scalability and cost-effectiveness.

• Train and test three ML algorithms to accurately classify edible and poisonous mushrooms using large datasets of mushroom images.

• Integrate the latest GPT technology into the IoT and ML system to enhance image classification and farm monitoring capabilities.

This study makes a significant contribution to the field of agricultural technology by developing an innovative, integrated IoT and AI system specifically designed to optimize mushroom farming in Jordan. The implementation of real-time monitoring and automated control of environmental conditions, coupled with advanced ML algorithms for mushroom classification, can solve critical challenges and present future opportunities in agriculture and non-agriculture applications. The methodologies (comparing three ML algorithms and depending on +5,000 images) adopted in the study hold the potential to transform agricultural practices, making them more efficient, resilient, and sustainable.

Materials And Methods

Study roadmap

This study follows a structured roadmap (Figure *1*) to develop and implement an integrated IoT and AI system for optimizing mushroom farming in Jordan. The process begins with an extensive literature review and interviews with key stakeholders, followed by comprehensive data collection of mushroom images from various sources. Subsequently, three state-of-the-art ML models (Visual Geometry Group 16 - VGG16, Inception Third Version - InceptionV3, and Residual Network - ResNet50) are trained and evaluated to obtain the optimal classifier for mushroom identification. Following this, the design and development of hardware and software components are presented for real-time environmental monitoring and image classification. Finally, the system is integrated with GPT-4o to enhance its capabilities, and the complete system is evaluated through rigorous testing and validation.

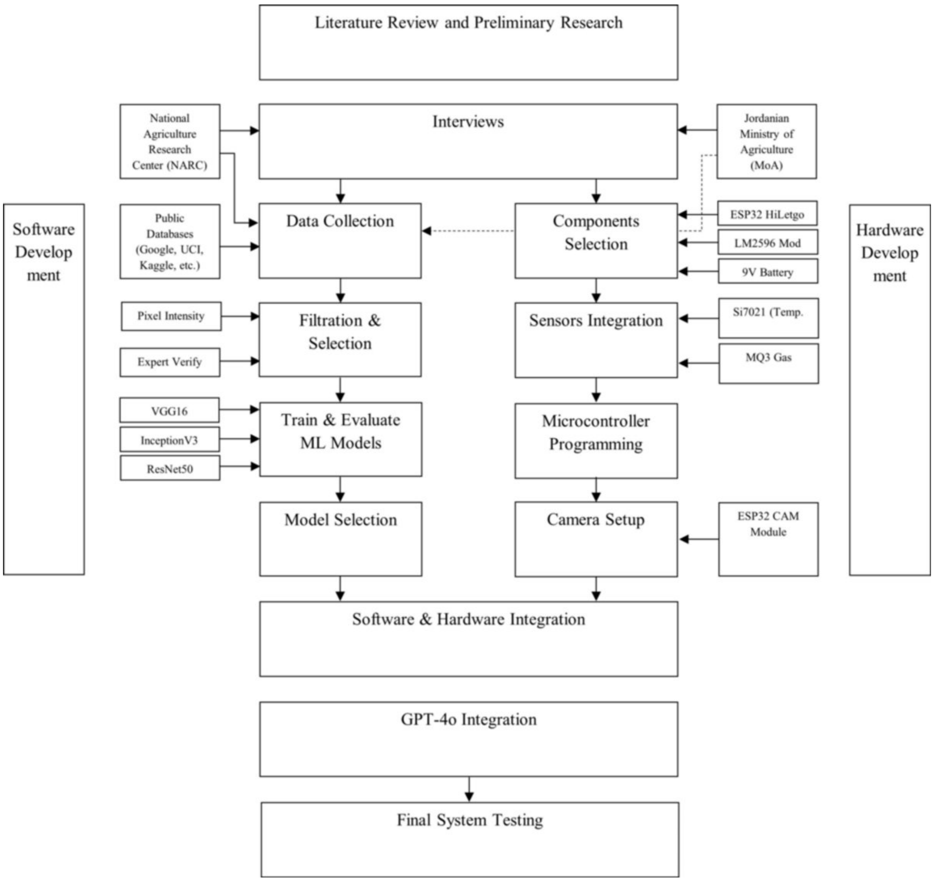

FIGURE 1: The study roadmap

Figure development: Author's own creation

Data collection

Interviews were carried out with the Ministry of Agriculture (MoA) and the National Agriculture Research Center (NARC) experts in Jordan. Interviews with various departments were conducted to understand the potential of the proposed system and to collect the data required for photos of edible and poisonous mushrooms from Jordanian farmers.

During these interviews, several key topics were discussed, focusing on the current problems faced by Jordanian farmers and the potential applications of modern technologies such as ML, IoT, and GPT-4o in agricultural solutions. Results from the interviews pointed out the advantage of such technologies in realizing early detection of diseases, hence helping timely intervention to reduce crop loss and poisoning rates by precisely differentiating between edible and poisonous mushrooms. Such technologies can help improve agricultural statistics for better planning and resource allocation. Other potential uses discussed included improving overall farm management (continuous measurements of soil temperature, humidity, and gas levels), optimizing resource use, and increasing crop yields through precise monitoring and automated control of environmental conditions.

A primary aim of the interviews was to obtain a diverse and representative set of images to train and test ML models for accurate classification of edible and poisonous mushrooms. The sources of the images included public databases (Google, UCI, Kaggle, etc.), contributions from local agricultural institutions, and direct collection from mushroom farms in Jordan. Kaggle dataset includes over 3,000 images [14]. With 61,068 instances, UCI dataset provided binary classification into edible and poisonous and helped with assessing (n = 1,203) images [15]. Moreover, using Google Images, (n = 819), photos were extracted from open-source domains.

The sources and the methodology for collecting the 5,071 images are displayed in Table *1*.

Source	Total Images	Edible Images	Poisonous Images
UCI ML Repository	1,203	702	501
Google	819	432	387
Kaggle	1,012	548	464
Interviews with NARC and MoA	1,001	573	428
Direct Collection Jordanian Farms	1,036	629	407
Total	5,071	2,884 (56.9%)	2,187 (43.1%)

TABLE 1: The sources of the collected data

Table development: Author’s own creation

UCI ML, University of California, Irvine Machine Learning Repository; NARC, National Agriculture Research Center; MoA, Ministry of Agriculture

In addition to assembling comprehensive image dataset, project placed significant emphasis on collecting environmental sensor data - parameters such as temperature, humidity, and gas concentrations - that accurately reflect the conditions within mushroom cultivation facilities in Jordan.

To ensure data relevance and quality, several approaches were utilized:

• Expert Consultation and Aggregated Data: Foundational environmental parameters and standard operating ranges were identified through interviews with specialists from the MoA and NARC. These expert insights provided a baseline for typical cultivation environments in the region.

• Direct Farm Data Logging: During field visits to local Jordanian mushroom farms, the team recorded real-time environmental readings alongside the image collection process. This approach enabled the capture of authentic, site-specific data under actual cultivation conditions.

• Prototype System Monitoring: As further detailed in the ‘Hardware Implementation’ section, the IoT prototype system - equipped with relevant sensors - was deployed during testing and validation phases to autonomously collect live environmental measurements.

Combining data from expert sources, direct field observation, and automated sensor readings, study ensured robust and contextually accurate dataset for system development and evaluation.

Filtration and selection

This phase ensures that the dataset used for training the ML models is of high quality, representative, and free from noise. This phase involved two main methods: pixel intensity analysis and expert judgment.

Within the first method, overexposed and underexposed images were identified by calculating the percentage of pixels with maximum and minimum intensity values, respectively, using equations (1) and (2).

$$OverexposureRatio = \frac{\sum pixels \geqslant 250}{Totalpixels}$$

$$UnderexposureRatio = \frac{\sum pixels \leq 5}{Totalpixels}$$

Overexposure and underexposure detection was employed in conjunction with the Python and OpenCV libraries. The criterion for overexposure detection involves calculating the ratio of pixels with maximum intensity values (typically those with a grayscale value of 250) to the total number of pixels. An image is flagged as overexposed if this ratio exceeds 20%, indicating an excessive presence of bright pixels that obscure critical details. On the other hand, images with a grayscale value of 5 were tested using the underexposure ratio, as shown in equation (2). An image is rejected if 20% of its pixels fall within this dark range, signifying a lack of sufficient lighting and detail.

Checking Figure 2, the initial dataset was 5,071 images collected from various sources: public databases, interviews, and direct field collections. Following this, the automated pixel intensity analysis efficiently processed these images, leading to the exclusion of 311 images identified as over- or underexposed. This resulted in 4,760 images proceeding to the expert verification stage. For the expert verification, the criteria established and validated through the intensive review of the n = 1,109 image sample were then meticulously applied to all 4,760 images. This comprehensive expert review further refined the dataset by excluding an additional five images that were found to be ambiguous, mislabeled, or lacking essential distinguishing features. This process culminated in a final dataset of 4,755 high-quality images ready for ML training and evaluation.

The verification test complements the technical automated filtration process in ensuring that the final dataset is not only contextually accurate but also technically sound. Every image is scrutinized for clarity, focus, and if it has apparent features that will distinguish edible from poisonous mushrooms. The criteria for this verification include the visibility of key morphological characteristics such as cap shape, gill structure, and color patterns. Images that are ambiguous, mislabeled, or lacking these critical features are excluded from the dataset. Experts document their assessments and provide feedback, which is used to refine the filtration thresholds and improve the overall data collection process.

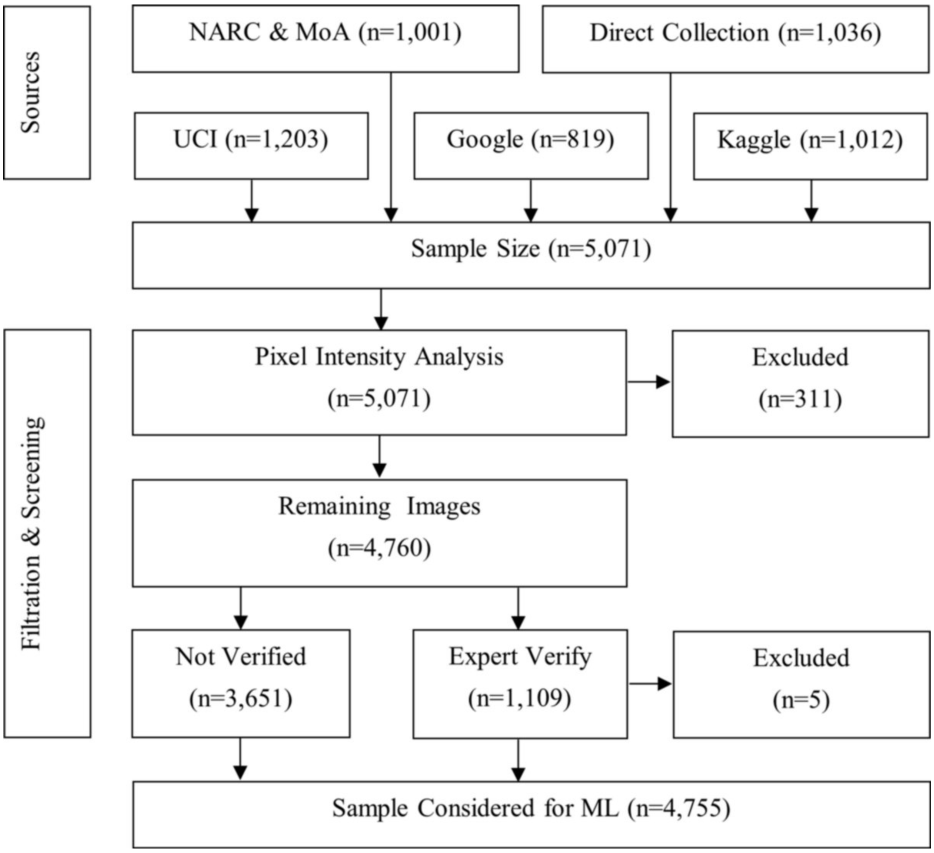

FIGURE 2: Flowchart for the filtration and screening process

Figure development: Author's own creation

NARC, National Agriculture Research Center; MoA, Ministry of Agriculture; ML, Machine Learning

Training, evaluation, and model selection

Three popular convolutional neural network architectures were chosen in the training and evaluation phase: VGG16, InceptionV3, and ResNet50. The high-quality dataset (n = 4,755) images balanced between edible and poisonous mushrooms serve as the foundation for training these models. VGG16 has a straightforward yet quite effective deep network structure of 16 weight layers; it has been applied to many image classification tasks and has had great success [16]. InceptionV3 evolved the GoogLeNet architecture with the use of inception modules to gain computational efficiency by applying multiple sizes of filters in one layer [17]. ResNet50 was the first to introduce residual learning, which allowed the vanishing gradient problem to train much deeper networks of 50 layers [18].

The training process of the three models was carefully designed for better performance on the mushroom classification task. The dataset was first divided into 70% for training and 15% for each validation and testing. Among others, random rotation, horizontal and vertical flips, and scaling were used as augmentation methods on the training set to make the model more robust against overfitting [19]. Aligning with Yosinski et al. [20], all models were initialized with the pre-trained weights from ImageNet, ensuring that transfer learning is used for faster convergence and higher accuracy. The models were fine-tuned using the Adam optimizer with an initial learning rate of 0.0001, which was reduced upon a plateau in validation loss to enhance model performance [21]. Cross-entropy loss function was employed to quantify classification errors. Early stopping was implemented to prevent overfitting, with training halting if validation loss did not improve for 10 consecutive epochs. During training, the models were evaluated on the validation set after each epoch, and the model achieving the highest validation accuracy was saved for final evaluation on the test set.

The confusion matrix plot (Figure *3*) compares VGG16, InceptionV3, and ResNet50 models in classifying mushrooms. VGG16 achieved 231 true positives (TP) and 257 true negatives (TN) with 117 false positives (FP) and 109 false negatives (FN). InceptionV3 showed improved accuracy with 248 TP and 265 TN, reducing FP to 101 and FN to 100. ResNet50 outperformed both with 264 TP and 280 TN, minimizing FP to 87 and FN to 83, making it the optimal model for mushroom classification due to its highest accuracy and least misclassifications.

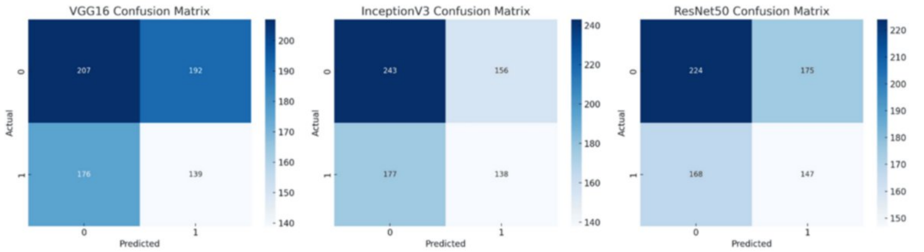

FIGURE 3: The confusion matrix comparing the three models

Figure development: Author’s own creation

To validate the selection, the training and validation accuracy and loss curves were plotted over 20 epochs. In Figure *4*, VGG16 shows steady improvement in both training and validation accuracy, stabilizing around 85%, with corresponding decreases in loss. InceptionV3 demonstrates a higher accuracy, reaching around 89%, with slightly lower loss values, indicating better performance. ResNet50 achieves the highest accuracy, approaching 91.5%, and exhibits the lowest loss among the three models. Additionally, the receiver operating characteristic (ROC) curves (Figure *5*) illustrate the performance of the three models across different thresholds. The ROC curve for VGG16, represented in blue, shows an area under the curve (AUC) of 0.62, indicating moderate performance. The InceptionV3 model, in green, exhibits better performance with an AUC of 0.75. The red ResNet50 curve performs best at an AUC of 0.838, showing the highest ability to differentiate between edible and poisonous mushrooms. The result aligns with [16], who indicate that generally, deeper architectures, such as ResNet50, achieve higher performance in classification for their advanced architecture and residual learning abilities.

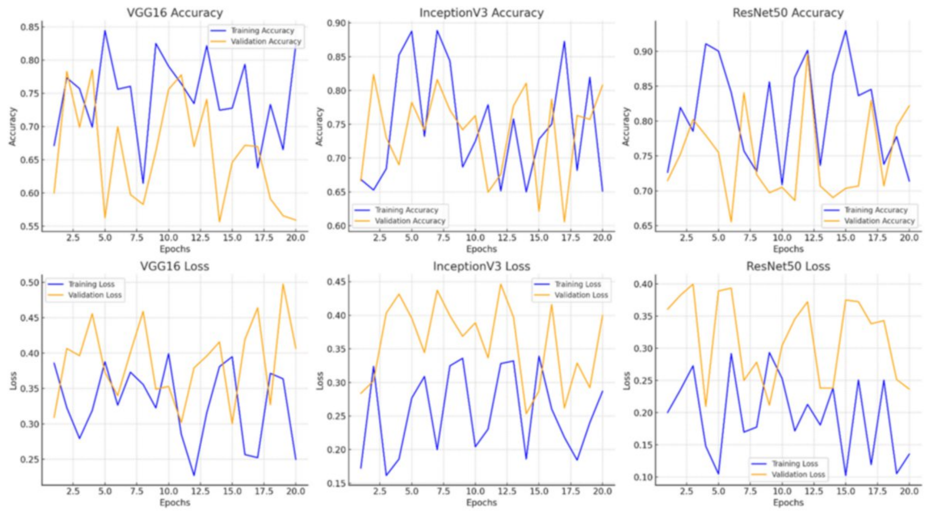

FIGURE 4: The accuracy and loss curves for the three models

Figure development: Author's own creation

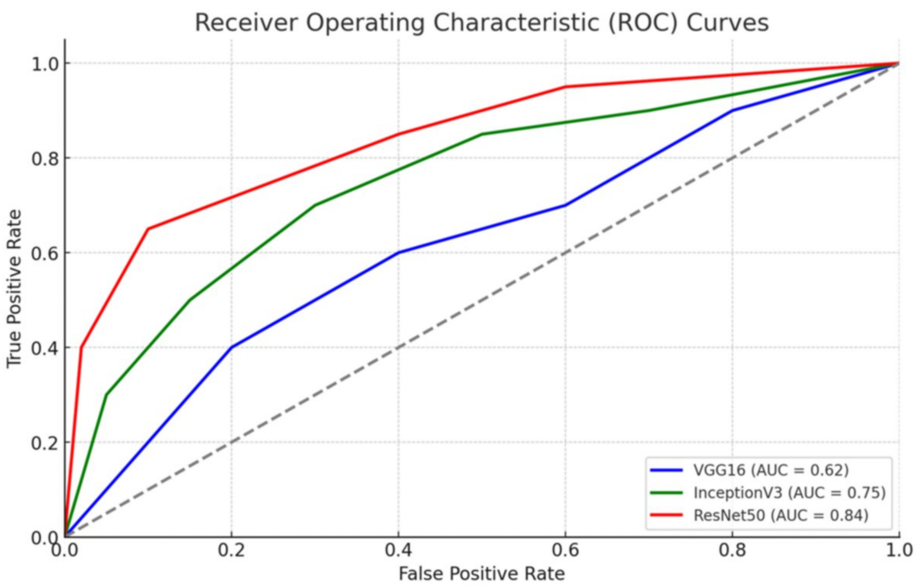

FIGURE 5: The receiver operating characteristic curves for the three models

Figure development: Author's own creation

AUC, Area Under the Curve

Hardware implementation

The hardware prototype of the integrated IoT-AI system was developed carefully with provisions for real-time monitoring of environmental conditions and the accurate classification of mushroom samples. Key components include the ESP32 HiLetgo WiFi module, Si7021 temperature and humidity sensor, MQ3 gas sensor, LM2596 step-down power supply module, and a 9V battery pack. The Si7021 sensor, positioned adjacent to the ESP32, monitors ambient temperature and humidity, while the MQ3 sensor, located next to the Si7021, detects gas levels for air quality monitoring. The detailed breadboard layout and schematic diagram are shown in Figure *6*. As indicated in Figure *1*, later on, the ESP32 CAM Module was integrated with the system.

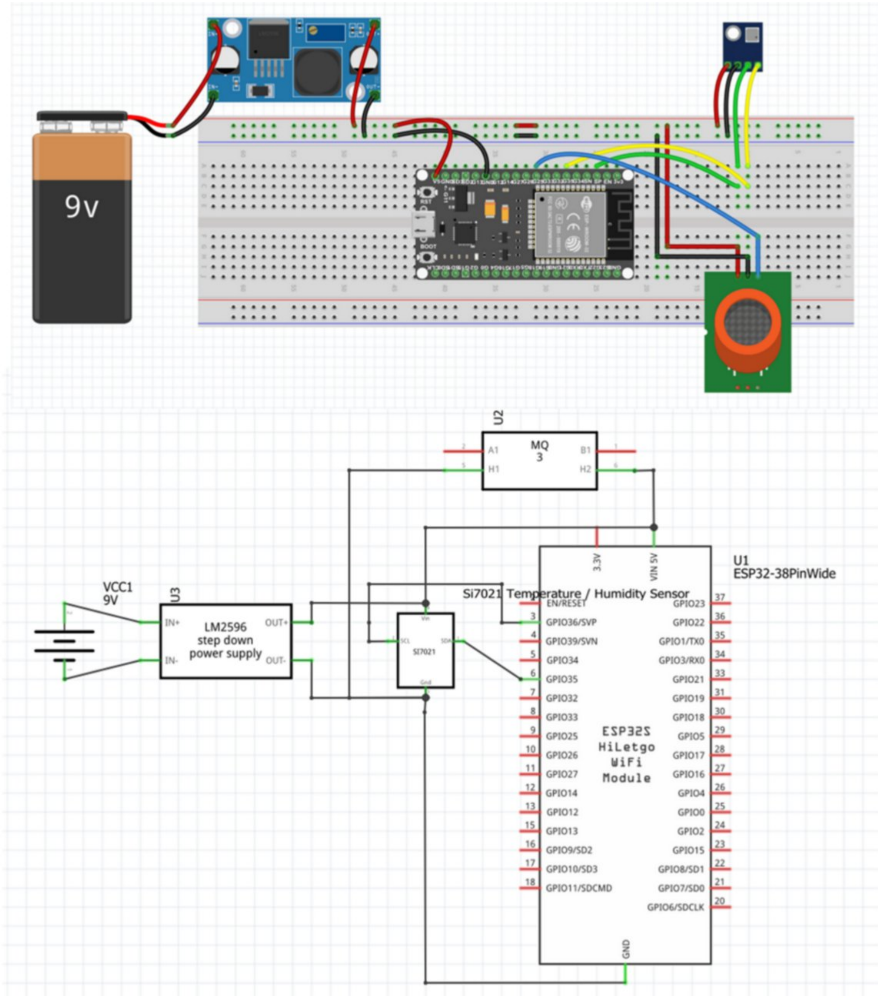

FIGURE 6: The breadboard layout (upwards) and schematic diagram (downwards) illustrate the configuration and wiring of the system before integrating the ESP32 CAM Module

Figure development: Author’s own creation

GPT-4o integration

The integration of GPT-4o into the IoT and ML system enhances image classification accuracy and provides advanced farm monitoring. This integration leverages GPT-4o's (OpenAI's newest model) to interpret sensor data and image analysis results. The data flow involves several key steps: real-time sensor data collection (temperature, humidity, gas levels) and image capture by the hardware components; preprocessing of this data; initial image classification using the ResNet50 model; and further analysis by GPT-4o. The interaction between the IoT system and GPT-4 is facilitated through the OpenAI API, with Python scripts handling data transmission via HTTP requests. Sensor data and the results from the ML image classification are formatted into structured prompts and sent to the GPT-4o model. The responses from GPT-4o are then integrated into the system’s dashboard, providing recommendations to the user. This process is illustrated in the data flow diagram (Table 2).

Step	Unit
Sensor Data Collection	Temperature (°C), Humidity (%), Gas levels (ppm)
Mushroom Image Capturing	Image (JPEG/PNG)
Preprocessing	N/A
Classification (ResNet50)	N/A
Formatting	Temperature (°C), Humidity (%), Gas levels (ppm), Image (JPEG/PNG), Prompts
GPT-4o Analysis	Text (direct user recommendations/insights), Sound (direct user voice alerts/recommendations), Code (Python - for system backend to generate dashboard logic or data visualizations), Images (e.g., data charts, visual components for dashboard, generated based on GPT-4o's analytical output for system use - JPEG/PNG)
Recommendations	Text, Sound
Real-Time Dashboard	Data charts, visual components for dashboard, generated based on GPT-4o's analytical output for system use (JPEG/PNG) - see Figure 8 for a sample

TABLE 2: The data flow diagram

ppm, Parts Per Million; JPEG, Joint Photographic Experts Group (image format); PNG, Portable Network Graphics (image format); N/A, Not Applicable; ResNet50, Residual Neural Network with 50 layers; GPT-4o, Generative Pre-Prained Transformer-4omni

Table development: Author’s own creation

Results from classification - ResNet50 - are combined with sensor data regarding temperature (°C), humidity (%), and gas levels (in ppm) to format structured prompts for GPT-4o. This analyzes the information and generates actionable recommendations and real-time interactive dashboards. The system's performance is evaluated based on the accuracy of GPT-4o's recommendations, system responsiveness, and user satisfaction. Performance evaluation is based on the accuracy of GPT-4o recommendations, system responsiveness, and user satisfaction. The average latency in collecting data from sensors for temperature, humidity, and gas was 100 milliseconds, while image classification using ResNet50 was 1,500 milliseconds at static and real-time.

The data formatting process, which prepares sensor data and classification results for GPT-4o analysis, added 3,000 milliseconds. The GPT-4o processing, which involves analyzing the formatted data and generating recommendations, took approximately 45,000 milliseconds. In total, the end-to-end response time from data collection to recommendation generation averaged 49,500 milliseconds (50 seconds). The previous timings were achieved using a high-performance computing system.

Results

Data analysis

The data preprocessing phase played a vital role in shaping the datasets for this study. Initially, a sizable collection of 4,755 mushroom images was curated and methodically prepared, forming the core of the training and evaluation process for the visual classification models. Alongside this, environmental sensor data underwent its own preprocessing pipeline. This dataset included representative information drawn from typical Jordanian mushroom farming environments (refer to the ‘Data Collection’ section for sources) as well as live, real-time readings captured by the prototype system (see ‘Hardware Implementation’). Incorporating this environmental data was essential - not only for enhancing and validating the monitoring aspects of the farm management system but also for supplying the contextual parameters required by the GPT-4o analysis and recommendation engine. This phase involved three critical steps: data cleaning, normalization, and augmentation. Initially, data cleaning was performed to ensure the quality of the dataset. Image data underwent a rigorous review, removing any images with poor resolution, noise, or incorrect labeling. Concurrently, sensor data, including temperature (°C), humidity (%), and gas levels (ppm), was checked for missing values, which were addressed using interpolation techniques, while outliers were identified using z-scores and managed appropriately. Several features in this dataset were normalized after data cleaning. The resizing of image data was done to standardize the images at 224 × 224 pixels for input into the ML models. Afterward, sensor data were scaled between 0 and 1 so that all would be on the same scale during model training. Random rotation, horizontal and vertical flipping, and brightness changes are data augmentation techniques applied to image data.

The statistical analysis phase employed several advanced techniques to ensure a robust understanding of the data. Initially, descriptive statistics (the mean, median, and standard deviation) were calculated. The mean temperature recorded was 22.5°C, with a standard deviation of 2.5°C, indicating a relatively stable temperature range suitable for mushroom cultivation. The humidity levels averaged 55.3%, with a standard deviation of 5.8%, reflecting moderate variability in moisture conditions. Gas levels showed a mean value of 150 ppm, with a standard deviation of 15 ppm, suggesting consistent air quality with minor fluctuations. Pearson correlation coefficients were then calculated to assess the relationships between different environmental variables, uncovering moderate correlations such as a 0.35 correlation between temperature and humidity. This suggests a potential joint impact on mushroom growth conditions. Additionally, an exploratory data analysis was conducted to identify any anomalies or trends that informed further preprocessing steps. For example, scatter plots (Figure 7) demonstrated the weak negative correlation of -0.12 between temperature and gas levels, indicating a limited direct impact on classification accuracy. These statistical techniques help guide the ML model training and GPT-4o analysis, ensuring better data reliability.

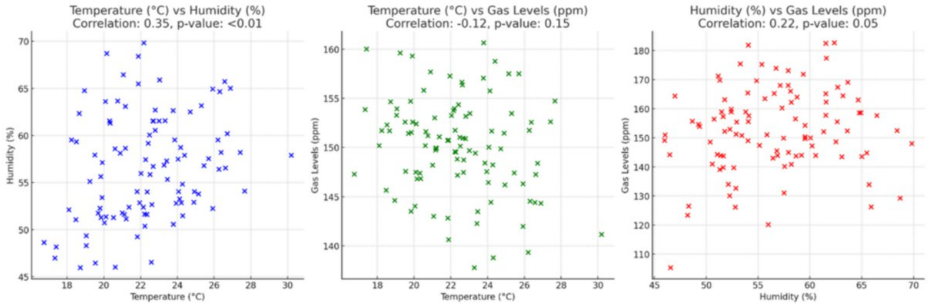

FIGURE 7: The scatter plots between the variables

Figure development: Author’s own creation

As previously stated, the performance of the ML models - VGG16, InceptionV3, and ResNet50 - was rigorously evaluated (Figures 4 and 5). This evaluation is critical to validate the efficacy of the models and to ensure their robustness and reliability for practical applications in mushroom farming. Compared to the rest, the ResNet50 model exhibited the highest performance, achieving an accuracy of 91.5%, with precision at 92.0% and recall at 91.0%. The F1-score of 91.5% underscores its balanced and high performance.

The ResNet50 model was programmed and tested through two distinct approaches to ensure user-friendly real-time application and static photo analysis. The first approach involved real-time (live) testing using a camera setup, while the second approach utilized static photo testing. Videos 1-3 demonstrate each approach. The static photo testing (image upload) achieved a higher accuracy of 91.5%, attributed to the controlled environment and higher computational power. The real-time testing was slightly lower than the static photo testing (89.8%) but was still highly effective for practical applications.

As summarized in Table 3, the evaluation of the three machine learning models on the test set reveals distinct performance differences. The ResNet50 model consistently outperformed the other architectures across all evaluated metrics, achieving the highest accuracy of 91.5%, a precision of 92.0%, a recall of 91.0%, an F1-score of 91.5%, and an AUC of 0.838. InceptionV3 demonstrated a moderate performance, surpassing VGG16, with an accuracy of 71.8% and an AUC of 0.750. VGG16 yielded the lowest scores, with an accuracy of 68.3% and an AUC of 0.620, indicating its comparatively weaker ability to classify edible and poisonous mushrooms in this study. These results clearly establish ResNet50 as the optimal model for the mushroom classification task.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
VGG16	68.3	66.4	67.9	67.2	0.62
InceptionV3	71.8	71.1	71.3	71.2	0.75
ResNet50	91.5	92	91	91.5	0.838

TABLE 3: Performance metrics of machine learning models on the test set

AUC, Area Under the Curve

GPT-4o implementation and user satisfaction

This section discusses the effectiveness of the GPT-4o integration, focusing on its performance in generating recommendations, facilitating user interaction through dashboards, and overall system responsiveness.

The primary role of GPT-4o in this system was to analyze sensor data and image classifications to generate actionable recommendations (text and sound) for mushroom farmers. The recommendations ranged from optimal environmental adjustments (e.g., temperature and humidity settings) to identifying potential disease outbreaks based on image analysis. Additionally, interactive dashboards powered by GPT-4o provided users with a user-friendly interface to monitor real-time data and obtain personalized insights. These dashboards (sample in Figure *8*) displayed critical information such as current environmental conditions, historical data trends (over time), and immediate alerts based on GPT-4o’s analysis.

The effectiveness of GPT-4o’s recommendations - delivered in both English and Arabic - was evaluated through a two-step process. Initially, agricultural experts reviewed its advice to determine whether it was scientifically accurate, applicable in practice, and consistent with well-established methods for mushroom cultivation. Following that, when the AI recommended specific actions - such as modifying environmental controls or responding to sensor alerts - these suggestions were tested in a prototype environment. The team then measured changes in sensor data and assessed whether the intended outcomes were achieved, thereby providing quantitative evidence of the system’s practical value. User satisfaction ratings were collected through surveys administered to 15 local farmers who participated in a hands-on demonstration and trial of the prototype system. These surveys utilized 5-point Likert scale (ranging from 1 = 'Very Dissatisfied' to 5 = 'Very Satisfied') to assess their perceived usability, the clarity of the text and voice recommendations, and the utility of the interactive dashboards. More than 70% of the farmers were satisfied and extremely satisfied with the text and voice recommendations. The satisfaction rates were lower for the interactive dashboards given their complexity and the time needed to be generated.

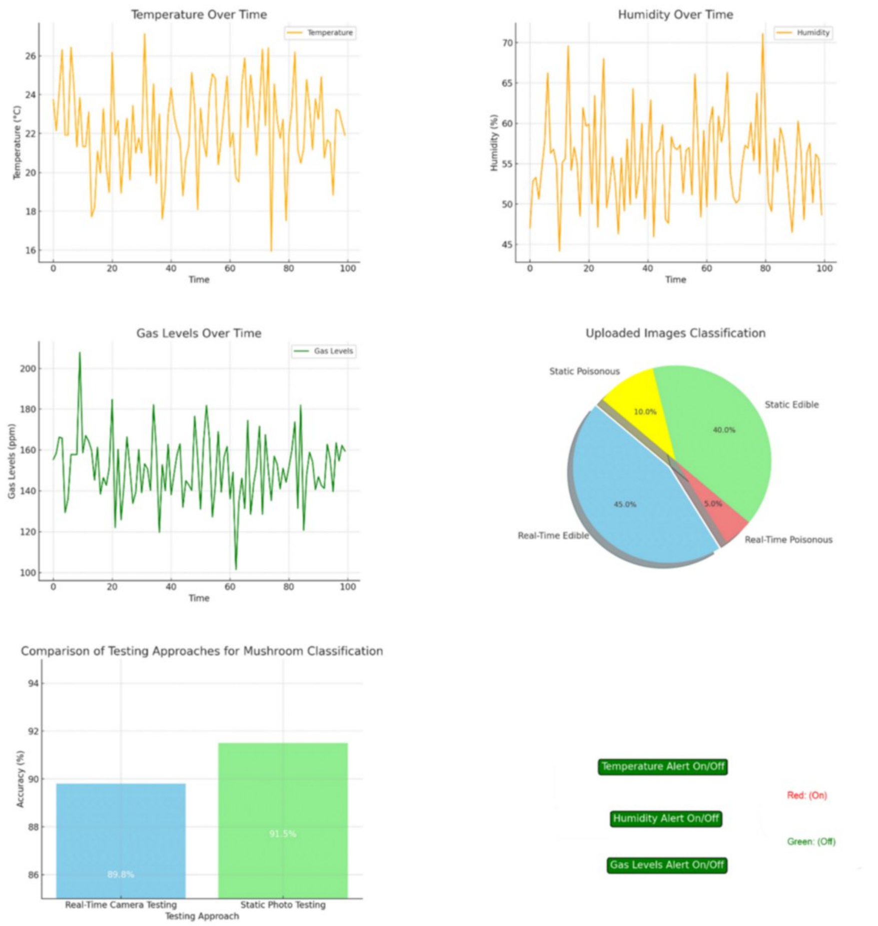

FIGURE 8: Sample of the interactive dashboard generated using GPT-4o model

Figure development: Author's own creation

VIDEO 1: Edible vs. poisonous mushroom detection (static/image upload method)

View video here: https://youtu.be/oW_q9zL3MIA

VIDEO 2: Edible vs. poisonous mushroom detection (dynamic/real-time camera method)

View video here: https://youtu.be/XNSgVrIUoyg

VIDEO 3: Edible vs. poisonous mushroom detection dashboard using ChatGPT 4o

View video here: https://youtu.be/t07jIdJmzTU

Discussion

Comparative analysis and implications

The current study presents significant advancements in mushroom farming technology through the innovative integration of IoT and advanced AI models, including ML and GPT-4o. Unlike previous works, such as those by Suresh et al. [22] and Angral [23], which focused solely on IoT without AI, or studies by Maurya and Singh [24] and Wibowo et al. [25] that utilized single AI models like SVM and decision tree, the current study tests a combination of VGG16, InceptionV3, and ResNet50, achieving a robust classification accuracy of 91.5% with ResNet50 architecture. Subsequently, GPT-4o was integrated alongside this high-performing ML model, building upon its classification results to leverage GPT-4o's distinct analytical capabilities for generating intelligent recommendations and interactive dashboards. This multi-model approach surpasses the 76.6% and 88.40% accuracy of Wibowo et al. [25] and Zahan et al. [26], respectively, and approaches the 100% accuracy of Rahman et al. [7], which integrated multiple AI techniques but did not utilize any GPT model. The inclusion of GPT-4o is particularly novel, providing intelligent recommendations (voice and text) and interactive dashboards (including On/Off alarms, as shown in Figure *8*) that enhance user interaction and decision-making. This study's comprehensive approach to real-time monitoring and farm automation, combined with rigorous performance evaluations (accuracy, precision, recall, and F1-score), underscores its superior methodology and outcomes.

Among the practical implications of the study is that it can lead to optimized environmental conditions, early disease detection, and improved yield quality. Furthermore, IoT-based real-time monitoring makes these adjustments dynamic concerning the conditions, making this system very adaptive. The possibility of extending this work as an open-source tool may make a difference in mushroom farming worldwide by democratizing easy-to-use solutions between farmers and researchers. Such a tool could democratize access to advanced agricultural technology, fostering a community of practice where shared data drive continuous improvements and innovations in mushroom farming. Finally, the current work can support the use of AI systems' recommendations and interactive dashboards in further applications.

The theoretical contributions foster the understanding of ensemble learning in agricultural applications. Moreover, integrating GPT-4o-a turbo model-brings a new dimension for agriculture AI, where NLP will be necessary for enhancing user interaction, data interpretation, and decision-making processes. This interdisciplinary approach highlights the importance of combining various AI techniques to address complex real-world problems, paving the way for future research that explores the integration of different AI paradigms in agricultural technology. The findings of this study could inspire new theoretical models and frameworks that capitalize on the strengths of diverse AI technologies, ultimately leading to more intelligent and adaptive agricultural systems.

While this study presents significant advancements in agricultural technology through the novel integration of IoT, AI, and GPT-4o, a critical practical consideration is the system's end-to-end response time. As detailed in the Materials & Methods section, the average latency from data collection to recommendation generation is approximately 50 seconds, a duration largely influenced by the GPT-4o processing phase. This substantial latency presents a limitation to the system's 'real-time' capabilities, particularly for highly time-sensitive events such as rapid disease outbreaks, sudden environmental shifts, or urgent alerts that necessitate immediate intervention. For scenarios requiring instantaneous decision-making and action, this delay could diminish the system's effectiveness and impact a farmer's ability to prevent crop loss or implement timely corrective measures. Therefore, while the system proves highly effective for continuous monitoring and less time-critical insights, its responsiveness for urgent, dynamic agricultural needs requires further optimization. Future development will critically focus on streamlining the processing pipeline, potentially through localized edge computing solutions or more efficient model deployment strategies, to significantly reduce this latency and enhance the system's true real-time applicability for critical alerts.

Prototypes and evidence of work

The components developed during this study were successfully integrated into a functional prototype, as depicted in Figure *9*. The hardware components of the prototype were detailed in the Hardware Implementation section. This physical implementation validates the practical applicability of the proposed IoT and AI system in real-world mushroom farming scenarios. The ML models and GPT-4o integration work were meticulously documented and saved as three demonstration videos: i) Static (image upload) video, ii) Real-time/live video, and iii) GPT-4o integration and analysis video.

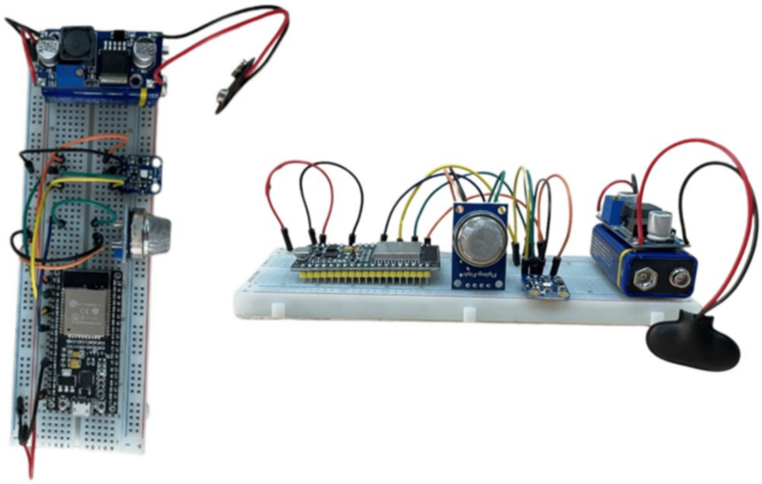

FIGURE 9: The created prototype

Figure development: Author's own creation

Conclusions

Mushroom farming holds significant importance in Jordan, both economically and nutritionally. The demand for mushrooms is steadily increasing due to their high nutritional value, including essential vitamins, minerals, and proteins. Moreover, mushroom farming presents an environmentally friendly option for agricultural diversification, utilizing agricultural waste and contributing to food security. This study has developed an automated system that integrates IoT and AI technologies (ML + GPT-4o) to enhance the efficiency, detectability, and sustainability of mushroom farming in Jordan. The data collection process initially resulted in a pool of 5,071 images. After implementing stringent filtering and screening protocols, this number was refined to 4,755 high-quality images suitable for further analysis. Subsequently, these images underwent extensive preprocessing procedures - including cleaning, normalization, and data augmentation - to ensure their readiness for ML model training. The ML models were trained and evaluated using statistical techniques, achieving the highest accuracy of 91.5% with ResNet50. The integration of GPT-4o provided voice and text actionable recommendations and an interactive dashboard with an advanced (On/Off) alert system.

This study is novel because it combines IoT, advanced AI models, and natural language processing through GPT-4o (most recent Turbo model) to address the complexities of mushroom farming. To the best of our knowledge, this study presents novel integration of these specific architectures (IoT, advanced AI models including ResNet50, and the GPT-4o model) for addressing the complexities of mushroom farming. Currently, there are no or low number of studies that have integrated GPT-4o with other ML systems to enhance detection and provide recommendations and visual dashboards. Furthermore, the work offers real-time monitoring and a static photo upload, which can be extended to further applications. Future research could explore the integration of drones for enhanced data collection and monitoring. Expanding the system to classify a wider variety of mushroom species could further improve its applicability and accuracy. Additionally, addressing privacy and security concerns will be critical to ensure the protection of users' data. However, the study had its limitations, including the reliance on good to high-quality images for accurate classification, which may only sometimes be available in real-world scenarios. A significant limitation identified is the end-to-end response time, which averages 50 seconds from data collection to recommendation generation. This latency, largely attributed to GPT-4o processing, impacts the system's real-time responsiveness, especially for urgent alerts requiring immediate action in a dynamic farming environment. Furthermore, the system's dependency on stable internet connectivity for IoT and GPT-4o functionalities could also pose challenges in remote farming areas.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Samer T. Abaddi

Acquisition, analysis, or interpretation of data: Samer T. Abaddi

Drafting of the manuscript: Samer T. Abaddi

Critical review of the manuscript for important intellectual content: Samer T. Abaddi

Supervision: Samer T. Abaddi

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Acknowledgements

Currently, the author does not have permission to publish or upload the data obtained from the National Agriculture Research Center (NARC) and the Ministry of Agriculture (MoA) of Jordan. However, the self-collected data can be uploaded to GitHub following manuscript acceptance.

References

1. Abaddi S: GPT revolution and digital entrepreneurial intentions. Journal of Entrepreneurship in Emerging Economies. 2024, 16:1902-1929. 10.1108/jeee-07-2023-0260
2. Kaushik K, Zindani D, Davim JP: Industry 4.0. SpringerBriefs in Applied Sciences and Technology. Springer, Singapore; 2019. 10.1007/978-981-13-8165-2
3. Ramirez C, Almulla Y, Joyce B, Huber-Lee A, Fuso Nerini F: An assessment of strategies for sustainability priority challenges in Jordan using a water-energy-food Nexus approach. Discover Sustainability. 2022, 3:23. 10.1007/s43621-022-00091-w
4. Akintuyi OB: AI in agriculture: A comparative review of developments in the USA and Africa. Open Access Research Journal of Science and Technology. 2024, 10:060-070. 10.53022/oarjst.2024.10.2.0051
5. Shahbandeh M: AI in agriculture market value forecast worldwide 2028. (2023). https://www.statista.com/statistics/1326924/ai-in-agriculture-marketvalue-worldwide/#:~:text=The%20value%20of%20artif....
6. Vailshery LS: Global Agricultural IIoT Market Value 2025. (2023). https://www.statista.com/statistics/1222813/worldwide-agricultural-industrial-iot-market-value/#:~:text=Agricultural%....
7. Rahman H, Faruq MO, Abdul Hai TB, et al.: IoT enabled mushroom farm automation with Machine Learning to classify toxic mushrooms in Bangladesh. Journal of Agriculture and Food Research. 2022, 7:100267. 10.1016/j.jafr.2021.100267
8. UNICEF: Water, Sanitation and Hygiene. (2024). https://www.unicef.org/jordan/water-sanitation-and-hygiene#:~:text=Challenges..
9. Qing J, Deng X, Lan Y, Li Z: GPT-aided diagnosis on agricultural image based on a new light YOLOPC. Computers and Electronics in Agriculture. 2023, 213:108168. 10.1016/j.compag.2023.108168
10. Akroush SN, Dhehibi B, Aw-Hassan A: Agricultural growth accounting and total factor productivity in Jordan. International Journal of Productivity Management and Assessment Technologies. 2016, 4:1-14. 10.4018/ijpmat.2016010101
11. ITA: Jordan - Agricultural Sectors. (2024). https://www.trade.gov/country-commercial-guides/jordan-agricultural-sectors.
12. Chang S, Wasser S: The Cultivation and Environmental Impact of Mushrooms. Oxford Research Encyclopedia of Environmental Science, Oxford, UK; 2017. 10.1093/acrefore/9780199389414.013.231
13. Bahn RA, Yehya AAK, Zurayk R: Digitalization for sustainable agri-food systems: Potential, status, and risks for the MENA region. Sustainability. 2021, 13:3223. 10.3390/su13063223
14. Edible and poisonous fungi. (2021). https://www.kaggle.com/datasets/marcosvolpato/edible-and-poisonous-fungi/data.
15. Wagner D, Heider D, Hattab G: Secondary Mushroom [Dataset]. UCI Machine Learning Repository. (2021). https://doi.org/10.24432/C5FP5Q.
16. Simonyan K, Zisserman A: Very deep convolutional networks for large-scale image recognition. arXiv:1409.1556. 10.48550/arXiv.1409.1556
17. Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z: Rethinking the inception architecture for computer vision. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA. 2016, 2818-2826. 10.1109/CVPR.2016.308
18. He K, Zhang X, Ren S, Sun J: Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA. 2016, 770-778. 10.1109/CVPR.2016.90
19. Krizhevsky A, Sutskever I, Hinton GE: ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems. 2012, 25:1097-1105.
20. Yosinski J, Clune J, Bengio Y, Lipson H: How transferable are features in deep neural networks?. Neural Information Processing Systems. 2014, 27:3320-3328.
21. Kingma DP, Ba J: Adam: a method for stochastic optimization. arXiv:1412.6980. 10.48550/arXiv.1412.6980
22. Suresh M, Srinivasan M, Gowri Shankar S, et al.: Monitoring and automatic control of various parameters for

mushroom farming. IOP Conference Series Materials Science and Engineering. 2021, 1055:012011. 10.1088/1757-899x/1055/1/012011
23. Angral P: Different automatic monitoring and controlling technique for mushrooms. Turkish Journal of Computer and Mathematics Education (TURCOMAT). 2021, 12:3363-3369.
24. Maurya P, Singh NP: Mushroom classification using feature-based machine learning approach. Proceedings of 3rd International Conference on Computer Vision and Image Processing. Chaudhuri B, Nakagawa M, Khanna P, Kumar S (ed): Springer, Singapore; 2020. 1022:197-206. 10.1007/978-981-32-9088-4_17
25. Wibowo A, Rahayu Y, Riyanto A, Hidayatulloh T: Classification algorithm for edible mushroom identification. 2018 International Conference on Information and Communications Technology (ICOIACT), Yogyakarta, Indonesia. 2018, 250-253. 10.1109/icoiact.2018.8350746
26. Zahan N, Hasan MZ, Malek MA, Reya SS: A deep learning-based approach for edible, inedible and poisonous mushroom classification. 2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), Dhaka, Bangladesh. 2021, 440-444. 10.1109/icict4sd50815.2021.9396845