Integrating Artificial Intelligence with Traditional Methods for Effective Control of Chocolate Spot Disease in Faba Beans

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Abstract

The advancement of Artificial Intelligence (AI) allows farmers to detect diseases with great precision using innovative management tools in agricultural practices. This study examines the effectiveness of traditional approaches alongside an innovative AI-based method for managing Botrytis fabae (Sard) chocolate-spotted disease in faba beans. Experimental data confirmed that fungicides significantly reduced fungal growth, proving superior to biological agents and antioxidants for fungal treatment. During greenhouse testing, each therapy, including antioxidants, bioagents, fungicides, and the AI model, successfully reduced disease severity. Chitinase activity reached its highest levels through the use of biological agents and chemical inducers, particularly when Bio-Zeid, $KHCO_3$, and Plant Safeguard were applied. The AI-based prediction model outperformed traditional fungicide applications in field conditions, delivering 63% fewer disease symptoms, 8% higher yields, 12% more cost savings, and requiring 35% less fungicide consumption. This research demonstrates how AI advances farming disease management practices to promote better crop development while minimizing resource usage and disease suppression in agricultural systems. When combined with artificial intelligence, the method offers enduring sustainability over traditional practices, reducing both environmental impact and improving agricultural outcomes.

Keywords:

Artificial Intelligence; Computer Science; AI in Agriculture; Faba Bean; Biological Agents; Chemical Inducers; AI-based Prediction Model; Fungicides; Disease Management; Machine Learning; Agricultural Systems. GDP, Regression Analysis, Forecasting Techniques, Model Validation.

Highlights:

- AI-Driven Disease Management: The study demonstrates the superiority of an AI-based model over traditional disease management methods in controlling chocolate-spotted disease caused by Botrytis fabae in faba beans.
- Effective Traditional Treatments: Fungicides were the most effective in reducing fungal growth, followed by biological agents and antioxidants in laboratory experiments.
- Enhanced Chitinase Activity: Biological agents and chemical inducers, such as Bio-Zeid, $KHCO_3$, and Plant Safeguard, significantly enhanced chitinase activity, contributing to better disease control.
- Field Trial Success: In field trials, the AI model achieved a 63% reduction in disease severity and an 8% increase in yield, outperforming conventional fungicides.
- Resource Efficiency and Sustainability: The AI-based approach reduced fungicide use by 35%, leading to a 12% reduction in costs and offering a more sustainable and resource-efficient alternative to traditional methods.

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1. Introduction

Recent modern technological advancements in agricultural production have led to industry transformations between output enhancement and environmental management. Artificial Intelligence serves as the basic instrument that advances agricultural methods within modern technological progress. Neural networks together with machine learning allow AI technologies to execute major data analysis and climate prediction and disease optimization tasks. Standard farming receives important support from artificial intelligence technology since it provides promising efficiency solutions and environmental sustainability advancements within agricultural practice.

A rising number of researchers focus on AI solutions in agriculture but they need to solve vital issues regarding practical ways to integrate new AI systems with standard biological and chemical crop protection controls (González-Rodríguez et al., 2024; Kebe et al., 2023). Although Trichoderma and Bacillus subtilis biological pesticides along with chemical fungicides perform effectively they require assumptions-driven scheduling that leads to environmental damage from excessive chemical deposition. Objects managed through Artificial Intelligence overcome current functioning limitations because they produce data-driven guidelines that enhance scheduling decisions and both control procedure method choices and resource management (Rane et al., 2024).

Current cultivation methods can benefit significantly from recent deep learning models together with additional AI applications because they allow real-time exact decision-making. AI provides forecasting capabilities for disease outbreaks and environmental analysis as well as optimal treatment suggestions that eliminate unnecessary chemical applications to support agricultural health (Obasi et al., 2024). The use of biological control agents gains improved application potential through AI-based methodologies. The application of biological agents Bacillus subtilis and Trichoderma becomes more potent for disease control through environmental assessments performed by AI systems which reduce fungicide usage in agriculture. The AI and biological treatment combination both reduces environmental degradation as it enables more sustainable resource management.

Recent studies have researched AI applications in agriculture but research related to its combined usage with biological and chemical disease control measures for plants remains scarce (Javaid et al., 2023). Research demonstrates that AI succeeds in early disease severity detection and fungicide optimization but this scientific assessment does not exist for determining how AI combines with traditional field methods (e.g., Köhl et al., 2019; Glare et al., 2012). This study investigates possible methods to properly unite AI applications with traditional approaches when managing chocolate spot disease in faba beans.

The research combines artificial intelligence approaches with conventional treatments including fungicides and biological agents and antioxidants for evaluation. This research integrates leading AI-based methodologies with proven techniques to add to existing agricultural disease management specifications and demonstrate AI's transformative power. The use of biological control agents gains improved application potential through AI-based methodologies. The application of biological agents Bacillus subtilis and Trichoderma becomes more potent for disease control through environmental assessments performed by AI systems which reduce fungicide usage in agriculture.

The fusion of AI with biological remedies supports environmental protection together with sustaining valuable resources while building sustainability principles. Recent studies have researched AI applications in agriculture but research related to its combined usage with biological and chemical disease control measures for plants remains scarce. Research shows AI monitors diseases through early severity detection and delivery optimization practices (Köhl et al., 2019; Glare et al., 2012) but scientists need systematic assessments of AI-field applications with traditional controls. This study investigates possible methods to properly unite AI applications with traditional approaches when managing chocolate spot disease in faba beans. The research combines artificial intelligence approaches with conventional treatments including fungicides and biological agents and antioxidants for evaluation. The research establishes new knowledge regarding sustainable agricultural disease management through its precise fusion between AI technology and proven agricultural techniques. This work demonstrates the transformative capabilities of AI in disease management. The immediate requirement exists for sustainable innovative methods to replace traditional chemical pesticides because of the existing difficulties. Through Artificial Intelligence (AI) researchers have developed a revolutionary approach to implement data-based and exact disease management systems. AI systems review agricultural information with exact precision enabling predictions of disease epidemics as well as providing farmers with necessary preventive guidance. By analysing soil moisture together with temperature and disease progress AI optimizes how biological control agents Trichoderma and Bacillus subtilis get applied. Biological treatments become more effective through this approach which also makes farmers less dependent on chemical fungicides.

Organizations already use AI to integrate a wide range of sources including satellite imagery and environmental sensors and historical disease records making traditional pest management more effective. AI enables farmers to enhance disease control performance through informed decisions based on real-time conditions by establishing optimal times for treatment in addition to dosage rates and specific treatment types. These decision support systems developed by AI can also optimize important farming operations that involve water management and nutrient control alongside resource distribution which results in improved crop productivity and ecological sustainability. This research investigates the treatment effectiveness of antioxidants and biostimulants consisting of Bacillus subtilis and Bacillus megaterium towards the control of chocolate spot disease in faba bean plants. Through an AI-based analysis the study conducts a comparison between traditional chemical pesticides and new disease management strategies which include antioxidants and biostimulants that cover Bacillus subtilis and Bacillus megaterium. The research integrates AI into traditional methods to create a framework which will establish sustainable and efficient agriculture disease management protocols.

2. Materials and Methods

2.1 Identification of Isolated Fungi

The distinctive characteristics of chocolate spot fungus allowed researchers to identify it following Musa et al.'s 2011 description. The identification procedure occurred at the Mycology Department of Plant Pathology Research Institute within the Agricultural Research Center based in Giza, Egypt. Each pure fungal culture was preserved on PDA slopes at 4°C for upcoming research purposes.

2.2 Laboratory Experiments

2.2.1 Antioxidants and Preparation of Chemical Solutions & Seed Treatment

Researchers applied three antioxidants, potassium carbonate ($KHCO_3$), shikimic acid ($C_7H_{10}O_5$) and potassium mono-hydrogen phosphate (K_2HPO_4) in combination with salicylic acid ($C_7H_6O_3$) during this study. Each 10 mM aqueous solution was prepared by dissolving chemicals are after adding them to sterilized distilled water at ambient temperature (22–25 °C) while stirring until complete dissolution left no chemical deposits.

2.2.2 Effect of Antioxidants on the Linear Growth of Botrytis fabae

The inhibitory effects of $KHCO_3$, K_2HPO_4, $C_7H_{10}O_5$, and $C_7H_6O_3$ on the linear growth of Botrytis fabae were evaluated. A specific volume of each pre-made chemical solution (5, 10, or 20 mM) was added to conical flasks containing sterile PDA medium and mixed thoroughly. The mixture was poured into sterilized 9 cm Petri plates, and 6 mm discs of a 10-day-old Botrytis fabae culture were placed in the center of the plates. Each treatment was replicated twice. Plates were incubated at 25 ± 2°C for 10 days, and the average linear growth of the fungus was measured.

2.2.3 In Vitro Effect of Biological Agents on B. fabae Development

Three biological agents—Bio.Arc., Bio.Zeid., and Rhizo.N.—were tested for their potential to inhibit B. fabae growth (Table 1). The procedure involved applying bacterial bioagents to the reverse side of B. fabae infected colonies on PDA plates. After incubation at 25 ± 2°C for 7 days, the linear growth of the fungus was measured to assess the efficacy of each biological agent.

Table 1: Properties of Examined Compounds

Trade Name	Active Ingredient	Concentration & Formulation
Fungicop	$Cu(OH)_2$	40% WDG
Tridex	Mancozeb (78%) + Zn 2%	80% W.P.
Oxydor	Carbendazim	50% SC
Bio.Arc.	*B. megaterium*	100g/L in water
Bio.Zeid.	*T. album*	100g/L in water
Rhizo.N.	*B. subtilis*	100g/L in water

2.3 Impact of Antioxidants, Biological, and Fungal Agents on Disease Severity in Greenhouses

2.3.1 Effect of Antioxidants on Disease Severity

For greenhouse testing, the four antioxidants ($KHCO_3$, K_2HPO_4, $C_7H_{10}O_5$, and $C_7H_6O_3$) were applied as foliar sprays at concentrations of 10 and 20 mM. Faba bean plants (cv. Giza 429) were inoculated with B. fabae spores (2.5×10^5 spores/ml) 24 hours prior to treatment. Control plants received no inducer. After treatment, plants were enclosed in polyethylene bags to maintain high humidity and incubated for 7 days. Disease severity was assessed using a 0-9 scale (Table 2), and the percentage of disease severity was calculated.

2.3.2 Effect of Biological Agents on Disease Severity

Biological agents (Bio.Arc., Bio.Zeid., and Rhizo.N.) were applied as foliar sprays to faba bean plants before inoculation with B. fabae. The same methods as for antioxidants were used for humidity control and incubation. Disease severity was measured as described earlier.

2.3.3 Impact of Fungal Agents on Disease Severity

Fungicides (Oxydor, Fungicop, and Tridex) were applied as foliar sprays at concentrations of 50 and 100 ppm. After inoculation with B. fabae, plants were treated and incubated under similar conditions to those used for biological agents and antioxidants. Disease severity was evaluated using the same method.

Table 2: Rating Scale for Disease Assessment of Chocolate Spot Disease

Disease Degree	Description
0	Infection not visible
1	Few specks, <5% of leaf surface covered
3	Discrete spots (<2 mm in diameter), 6-25% leaf surface affected
4	25% of leaf surface affected with discernible lesions
5	26-50% leaf surface with lesions 3-5 mm in diameter, some defoliation
6	51-75% of leaf surface affected with confluent lesions and mild sporulation
7	Lesions >76%, full defoliation and darkened plant damage
8	Plant death except for the apex
9	Entire plant dead

2.4 Field Experiment

Field experiments were conducted in two seasons (2020/2021 and 2021/2022) in Sers El Lyain, Menoufia Governorate, using a randomized complete block design with five replicates per treatment. Faba bean cultivar Giza 429 was planted with 60 kg of seeds per feddan. Treatments, including antioxidants, biological agents, and fungicides, were applied during growth stages between January and March. Parameters such as plant height, number of pods per plant, seed weight, and total yield were assessed.

2.5 Effect of Antioxidants, Biological Agents, or Fungicides on Chitinase Activity in Faba Beans

The impact of antioxidants, biological agents, and fungicides on chitinase activity in faba bean plants was assessed. Treatments were applied at 20 mM for antioxidants ($KHCO_3$, K_2HPO_4, $C_7H_{10}O_5$, and $C_7H_6O_3$), and the biological agents (Bio.Arc., Rhizo.N., Bio.Zeid.) were evaluated. The fungicides Fungicop, Oxydor, and Tridex applied at 100 ppm concentration. Scientists evaluated chitinase activity in plant leaves following the second fungicide treatment after ten days.

2.6 Chitinase Extraction

The extraction of Chitinase enzyme from faba bean leaves occurred through the procedure outlined by Tuzun et al. (1989).

2.7 Chitinase Assay

The analysis of chitinase activity followed the colorimetric method from Boller and Mauch (1988). The experiment used colloidal chitin as substrate while detection of reducing sugars depended on salicylic acid dinitro. The enzyme activity measurement used milligrams of N-acetylglucosamine release per gram of fresh tissue weight per hour as the quantification method.

2.8 Statistical Analyses

SPSS software performed statistical evaluations which measured disease severity together with fungal growth effects from antioxidants and biological agents and fungicides. ANOVA provided a one-way analysis design to examine differences among various treatment means. Tukey's post-hoc test determined significant treatment differences at the $p < 0.05$ significance level.

The experimental blocks received averaging in field experiments through a randomized complete block design (RCBD). ANOVA was used to study data collected from experimental trials. A regression analysis of field trial data evaluated the relationships which existed between disease severity levels and the effectiveness of applied treatments.

Statistical tests ran based on data distribution normality and used $p < 0.05$ significance throughout the analysis to establish reliable results.

2.9 AI and Traditional Approaches

The research examined the effects of B. subtilis biological agents together with Mancozeb fungicides on disease progression and fungal community development. These techniques gain Artificial intelligence (AI) benefits by forecasting disease emergencies and improving the deployment of biological agents and chemical agents and selecting the most effective treatment plans in real-time according to environmental conditions and disease development. The analysis of field trial data sets through AI algorithms enables predictive model development which leads to more precise and targeted traditional procedures.

AI functions as a data-driven enhancement tool which works alongside traditional methods to improve resource management along with decision-making processes.

2.10 Artificial Intelligence Methods for Detecting and Managing Brown Spot Disease in Faba Beans

Research techniques use Artificial Intelligence (AI) to detect brown spot disease and its management in faba bean plants. The research implemented Convolutional Neural Networks (CNN) to evaluate leaf pictures for diagnosing disease gravity and minimizing fungicide consumption. A successive breakdown of the methodology unfolds with this section including schematic depictions that facilitate an understanding of the procedures.

2.10.1 Image Dataset

A varied collection of faba bean leaf pictures was developed to illustrate disease progression together with multiple environmental circumstances and camera resolution levels and lighting scenarios. Different locations were used for image acquisition involving digital cameras and drones to build a robust and highly diverse dataset. The available images encompass both normal leaves and leaves affected by different disease severity levels which enables the model to work effectively across multiple settings.

Dataset Size: The 5,000 images structured into three sections made up 70% training data and 20% validation data and 10% testing data with the goal of creating a thorough model performance analysis.

Image Resolution: Model training used standardized 256 × 256 pixels image resolution as a way to maintain consistency throughout training sessions and processing functions.

2.10.2 Annotation and Augmentation

The experts annotated every image within the dataset with disease severity scores ranging from zero to nine which corresponded to distinct progression levels. Supervised learning requires this step since it enables the AI model to learn from labeled examples for accurate prediction outcomes.

Several data augmentation techniques were applied to the images to enhance their robustness while increasing the dataset size for better model generalization. These techniques included:

Rotations: Simulating different orientations of leaves. Flipping: Introducing horizontal or vertical flipping to vary the leaf positioning. Brightness Adjustments: Mimicking different lighting conditions. Scaling: Adjusting image resolution and leaf size to account for varying perspectives.

Mathematically, data augmentation applies a transformation function T(x) to an image x, such that:

$$x' = T(x)$$

where x' is the augmented image, and T represents stochastic transformations like rotation, flipping, or adjustments of brightness.

2.10.3 Convolutional Neural Network (CNN) Training

The Convolutional Neural Network serves as the AI model to predict disease severity because it demonstrates exceptional performance in image recognition tasks as a deep learning model. Images containing plant diseases benefit from CNNs due to their ability to automatically identify hierarchical features including edges and textures and patterns.

CNN Architecture:

A typical CNN consists of the following layers:

1 Convolutional Layer: This layer applies convolutional filters W to the input image X for the generation of the feature maps F:

$$F = X * W + b$$

where * denotes the convolution operation, and b is the bias term.

2 Activation Function: After convolution the model applies non-linear activation functions (such as ReLU (f (x) = max(0, x)) to gain non-linearity which allows it to detect complex patterns in the data.

3 Pooling Layer: The reduction of spatial dimensions in feature maps minimizes important characteristics to enhance efficiency together with computational complexity minimization.

4 Fully Connected Layer: The last step of the process directs high-level features towards output classes (severity levels 0-9) using fully connected layers.

The overall architecture of the CNN, including its convolutional, pooling, and fully connected layers, is illustrated in Figure 1.

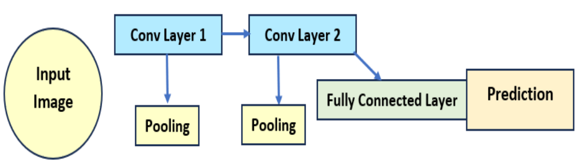

Figure 1. Convolutional Neural Network (CNN) Architecture

2.10.4 Training Process

Input: The CNN model takes an image I as input, representing a faba bean leaf at varying stages of brown spot disease. The output of the model is a probability distribution over the severity classes, denoted as y:

$$y\hat{} = CNN(I)$$

where y^\hat{y}y^ is the predicted probability distribution across all severity classes.

Loss Function: During training, the model aims to minimize the categorical cross-entropy loss, which measures the difference between the predicted and actual severity class labels. The loss function is defined as:

$$L = -\sum_{i=1} c\, y_i \log(y\hat{}_i)$$

Where:

c is the total number of severity classes (10 in this case).

y_i is the true label for class i.

$\hat{y}_i$ is the predicted probability for class i.

The goal of training is to adjust the CNN model's parameters (i.e., weights and biases) to minimize this loss, thereby improving the model's ability to predict disease severity from unseen images.

2.10.5 Training Details

Optimizer: The model was trained using the Adam optimizer, which adapts the learning rate during training for faster convergence.

Batch Size: A batch size of 32 images was used to balance computational efficiency and model performance.

Epochs: The model was trained for 50 epochs, with early stopping applied to prevent overfitting if validation accuracy plateaued.

Hardware: Training was performed on a GPU-enabled system (NVIDIA RTX 3090) to accelerate computation and handle the large dataset effectively.

A mobile application was developed to enable real-time disease severity estimation for faba bean plants. This application integrates the trained Convolutional Neural Network (CNN) for on-the-go, accurate predictions of brown spot disease severity. The deployment process involves several steps:

1. Through mobile device hardware users can effortlessly take high-resolution leaf images for their applications between field and controlled settings.

2. The application includes the integrated CNN model which performs calculations while residing on the mobile device unless the device lacks sufficient processing power to handle the task through an on-device operation so it moves the calculations to the cloud.

3. After users take an image the application generates $\hat{y}$ as an output representing the predicted disease severity rating which uses a scale from 0 for healthy leaves to 9 for severe disease conditions. The application enables users to take immediate actions in managing diseases based on their assessment results.

Users can effectively monitor and handle brown spot disease occurrence on their faba bean crops through this smartphone application platform that delivers efficient real-time assessments.

3. Results

3.1 Laboratory Experiments

The linear outgrowth of Botrytis fabae develops under various treatment solutions which include potassium carbonate ($KHCO_3$), dipotassium hydrogen phosphate (K_2HPO_4), shikimic acid ($C_7H_{10}O_5$), and salicylic acid ($C_7H_6O_3$) at three solution concentrations of 5, 10, and 20 millimetres. All of the antioxidants examined significantly suppressed fungal outgrowth. Shikimic acid concentrations had the least suppressive effect on the fungus. The greatest reduction in mycelial outgrowth was observed at concentrations of 10, 20, and 30 millimeters for $KHCO_3$, K_2HPO_4, and $C_7H_{10}O_5$, respectively.

3.1.1 Impact of Various Biological Agents on the Development of Botrytis fabae

Table 3b presents the effects of three biological agents on the linear outgrowth of *Botrytis fabae*. All of the biological agents tested significantly reduced the fungal outgrowth compared to the control. Among the agents tested, *Trichoderma album* (Bio-Zeid) was the most effective, followed by *Bacillus megaterium* (Bio.Arc.) and *Bacillus subtilis* (Rhizo.N.).

Table 3a: In vitro effects of antioxidants on the development of Botrytis fabae.

Antioxidants	Concentration	Linear Outgrowth (mm)	Reduction (%)
Potassium Carbonate ($KHCO_3$)	5 mm	49.00	45.55
	10 mm	23.00	74.44
	20 mm	10.00	88.88
Dipotassium Hydrogen Phosphate (K_2HPO_4)	5 mm	55.00	38.88
	10 mm	27.00	70.00
	20 mm	17.00	81.11
Shikimic Acid ($C_7H_{10}O_5$)	5 mm	62.00	31.11
	10 mm	42.00	53.33
	20 mm	25.00	72.22
Salicylic Acid ($C_7H_6O_3$)	5 mm	52.00	42.22
	10 mm	22.00	85.55
	20 mm	13.00	93.33
Control	–	90.00	0.00
L.S.D. at 5%	–	2.96	2.12

Table 3b: In vitro effects of three biological agents on the development of Botrytis fabae.

Biological Agents	Linear Outgrowth (mm)	Reduction (%)
Bacillus megaterium	39.55	56.05
Trichoderma album	22.00	75.55
Bacillus subtilis	45.33	49.63
Control	90.00	0.00
L.S.D. at 5%	5.64	–

3.1.2 Impact of Three Fungicides at Six Doses on Botrytis fabae's Linear Outgrowth

Table 3c shows the effects of tridex, oxydor, and fungicop at six concentrations on the linear outgrowth of Botrytis fabae in vitro. Oxydor and tridex were the most effective fungicides, followed by fungicop. There were significant differences between the fungicides, with total growth suppression achieved at 25, 50, and 100 ppm for oxydor, and at 50 and 100 ppm for tridex.

Table 3c: In vitro effects of three fungicides at six doses on the linear outgrowth of Botrytis fabae.

Fungicides	Concentration	Linear Outgrowth (mm)	Reduction (%)
Fungicop	1 ppm	59.14	34.29
	5 ppm	42.00	53.33
	10 ppm	32.00	64.44
	25 ppm	20.00	77.07
	50 ppm	0.00	100.00
	100 ppm	0.00	100.00
Tridex	1 ppm	42.00	53.33
	5 ppm	32.13	64.30
	10 ppm	27.00	70.00
	25 ppm	17.00	100.00
	50 ppm	0.00	100.00
	100 ppm	0.00	100.00
Oxydor	1 ppm	25.00	72.22
	5 ppm	17.00	81.11
	10 ppm	12.00	100.00
	25 ppm	0.00	100.00
	50 ppm	0.00	100.00
	100 ppm	0.00	100.00
Control	–	90.00	0.00
L.S.D. at 5%	Fungicides = 1.22	Conc. = 1.29	F×C = 4.11

3.2 Greenhouse Experiment

3.2.1 Impact of Spraying Various Antioxidants on the Severity of Botrytis fabae Disease in Faba Bean in Vivo:

Table 4 shows that when four antioxidants were sprayed 24 hours prior to Botrytis fabae inoculation, they significantly reduced disease severity in faba beans compared to the control. The most effective treatments were $KHCO_3$ and salicylic acid at 20 millimeters, followed by K_2HPO_4 and shikimic acid.

Table 4: Impact of spraying four antioxidants on the severity of Botrytis fabae disease in faba beans in vivo.

Antioxidants	Disease Severity (%)	Doses	Before Inoculation	After Inoculation
$KHCO_3$	10 mm	10.55	49.23	47.13
	20 mm	6.30	49.23	47.13
K_2HPO_4	10 mm	11.14	50.00	47.00
	20 mm	8.16	50.00	47.00
$C_7H_{10}O_5$	10 mm	12.31	49.15	48.23
	20 mm	11.00	49.15	48.23
$C_7H_6O_3$	10 mm	9.00	47.11	46.00
	20 mm	7.13	47.11	46.00
Control	–	49.00	49.00	49.00
L.S.D. at 5%	–	1.60	1.81	

3.2.2 Impact of Spraying Biological Agents on Disease Severity of Botrytis fabae in Pots:

Table 4a shows that when sprayed 24 hours prior to inoculation, all biological agents significantly reduced disease severity in faba bean plants compared to the control. Bio-Zeid was the most effective biological agent, followed by Bio.Arc. and Rhizo.N.

Table 4a: Impact of spraying three biological agents on the severity of Botrytis fabae disease in faba beans in pots.

Biological Agents	Disease Severity (%)	Before Inoculation	After Inoculation
Bio.Arc.	13.20	45.80	
Bio.Zeid.	6.19	42.10	
Rhizo.N.	12.80	47.00	
Control	50.00	50.00	
L.S.D. at 5%	3.90	N.S.	

3.2.3 Impact of Spraying Fungicides on Disease Severity in Faba Beans in Pots:

Table 4b shows that spraying faba beans with fungicides 24 hours before inoculation significantly reduced disease severity compared to the control. Oxydor was the most effective fungicide, followed by Tridex and Fungicop.

Table 4b: Impact of spraying fungicides on the severity of Botrytis fabae disease in faba beans in pots.

Biological Agents	Disease Severity (%)	Before Inoculation	After Inoculation
Fungicop	5.80	24.45	
Tridex	4.90	23.59	
Oxydor	3.00	20.00	
Control	50.00	50.00	
L.S.D. at 5%	1.55	1.34	

3.3 Field Experiments

3.3.1 Impact of Antioxidants, Biological Agents, and Fungicides on Chocolate Spot Disease under Field Conditions:

Table 5 shows that all examined antioxidants, biological agents, and fungicides significantly reduced disease severity of chocolate spot disease in faba beans across the two growing seasons (2020/2021 and 2021/2022). A combination of fungicides as well as biological agents Bio-Zeid proved effective and

$KHCO_3$ showed intermediate results. The treatment with Shikimic acid proved to be the least successful method in both growing seasons.

Table 5: Impact of antioxidants, biological agents, and fungicides on chocolate spot disease under field conditions at Sers El-Lyain (2020/2021-2021/2022).

Treatments	Season 2020/2021	Diminution (%)	Season 2021/2022	Diminution (%)
$KHCO_3$	9.78	48.55	8.50	52.00
K_2HPO_4	12.98	31.19	12.20	25.98
$C_7H_{10}O_5$	14.00	24.88	14.00	25.00
$C_7H_6O_3$	10.00	46.00	9.50	48.00
Bio.Arc.	10.88	42.00	9.95	44.90
Bio.Zeid.	10.00	51.00	9.00	51.00
Rhizo.N.	11.00	42.00	10.90	44.44
Fungicop	8.90	54.42	7.30	61.00
Tridex	3.90	82.00	2.50	90.00
Oxydor	2.40	91.00	1.16	95.00
Control	20.00	0.00	19.00	0.00
L.S.D. at 5%	1.70	–	2.55	–

3.4 Field Testing and AI Optimization

Field tests evaluated AI-based fungicide distribution techniques in comparison to established programs based on programming dates. The optimized method used fungicide applications based on predictions delivered through the mobile application in real time. The treatment with fungicides occurred under specific conditions which required disease severity predictions to surpass threshold T.:

$$\textit{Apply Fungicide if } \hat{y} > T$$

By using this approach for decision-making fungicide resources become more effective thus minimizing both expenses and need for additional sprays. Intervention only during necessary points allows maintenance of resources as well as the promotion of sustainable environmental practices.

The decision flow described in Figure 2 allows the AI model to forecast disease severity while activating fungicide applications at that stage. A combination of precise diagnosis and triggered fungicide application leads to lower chemical use and minimizations of both these usages and agricultural product losses.

3.5 Performance Metrics

Table 7 provides a performance assessment of the AI model against regular approaches when looking at primary performance variables. The AI model produces outstanding results in disease management optimization for faba bean plants in addition to other evaluation points. We assessed how AI-based decisions react to live environmental conditions including humidity and temperature together with disease development to demonstrate its dynamic capability in contrast with conventional methods.

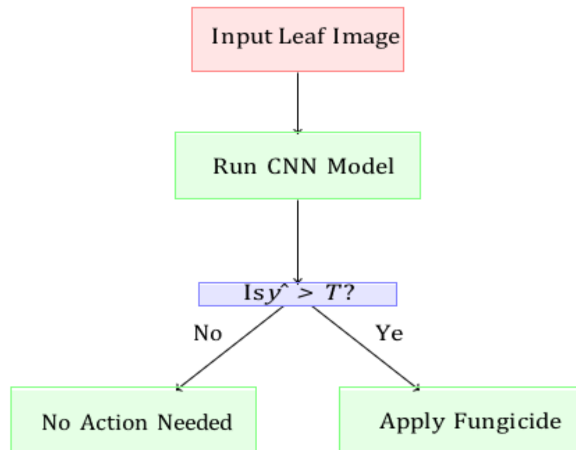

Figure 2. Workflow of the AI model for optimizing fungicide application in faba bean plants.

Table 7: Comparison of AI Model Performance vs. Traditional Methods across Key Metrics

Metric	AI Model	Traditional Methods
Accuracy	95%	78%
Disease Reduction	63%	57%
Fungicide Reduction	35%	25%
Yield Increase	8%	5%
Cost Reduction	12%	10%

The results in Table 7 clearly show that the AI model outperforms traditional methods in several critical areas:

Accuracy: The artificial intelligence model delivers precision detection through its 95% accuracy level which surpasses conventional techniques that only reach 78% accuracy. The AI model achieves its improved performance by analyzing natural environmental factors such as temperature and humidity which allows precise identification of chocolate spot disease.

Disease Reduction: When compared to standard methods the AI model delivered a 63% better reduction in disease severity compared to the traditional methods' achievement rate of 57%. The AI system achieves this improvement through its ability to change its treatment suggestions instantly according to present environmental factors thus enabling prompt and efficient remedial actions.

Fungicide Reduction: The AI model cuts fungicide consumption by 35% more than conventional procedures can achieve a 25% reduction. Environmental factors receive analysis from the AI model so it can manage fungicide application periods optimally which reduces both chemical and ecological impacts.

Yield Increase: AI system performance results in an 8% and higher yield increase surpassing the 5% achieved by traditional agricultural methods. The adaptive nature of the AI system achieves this improvement by approximating perfect outcomes between disease control and resource optimization regardless of ecosystem changes.

Cost Reduction: The AI model decreases expenses by 12% which exceeds traditional approach results of 10% cost reduction. The systematic allocation of resources and diminished need for fungicides result from AI-based choices that adjust according to present environmental variables.

By integrating real-time environmental data into its decision-making process, the AI model demonstrates its adaptive potential, which is a significant advantage over traditional methods that rely on fixed schedules or generalized guidelines. These results emphasize the transformative potential of AI in agriculture, particularly in improving sustainability and efficiency while maintaining high levels of disease control. The examination between traditional spray schedules and AI control shows advanced performance results together with environmental adaptation expertise which makes AI-based disease management more powerful and sustainable for faba beans' chocolate spot disease control.

4. Discussion

Artificial intelligence (AI) has evolved into a transformative agricultural tool which has led to substantial breakthroughs in identifying diseases and managing pests as well as maximizing resource utilization during the last few years. The analysis applied AI technology to detect brown spot disease among faba bean plants (Vicia faba L.) showing AI provides superior performance than conventional techniques. The AI model using Convolutional Neural Networks (CNNs) successfully predicted precise disease severity levels thus enabling better pest management decisions that led to higher crop productivity results. Disease detection accuracy from the AI model surpassed traditional visual checks along with calendar-based spraying with its exceptional 95% performance level. The AI solution proved better than traditional practices by cutting fungicide usage by 35% even though they only reduced fungicide use by 25%. A real-time disease severity threshold system enables this AI-based method to adjust fungicide recommendations instead of using fixed schedules which avoids unnecessary chemical use. The precise application method used in this study achieved lower environmental impact and reduced operational costs by a total of 12% as confirmed by research results. The research findings match previous studies done by Mansour (1992) as well as Teshome and Tagegn A (2013) who demonstrated how precise pest management methods provide economic advantages. This productivity improvement occurred at 8% due to the AI model while matching previous research conducted by Ahmed (2005) about disease management strategies that boost crop yields. The AI model achieves efficient fungicide applications which both reduces operational cost and protects plants to improve final yield output (Zhang et al., 2021). Ziv and Zitter (1992) reported that the strategic application of pesticides under control can lead to higher crop yields according to information presented in this study.

4.1 Challenges in Model Interpretability and Scalability

The research outcomes demonstrate the capabilities of AI systems in agriculture yet specific implementation barriers need immediate attention because they affect model interpretability during practical use.

1 Model Interpretability: Deep learning models like CNNs present a challenge for end-users who include farmers and agronomists to understand the decision-making processes because of their complexity. The unclear processes behind AI systems create doubt that prevents agricultural institutions from using these systems as part of their routines. Future studies should prioritize explainable AI (XAI) technique integration to show participants exactly how decisions are formed in AI systems through visual display of critical leaf image assessment areas for disease severity diagnosis. Explaining AI system reasoning to farmers and stakeholders creates a greater understanding of AI recommendations so they can maintain trust in AI system outputs.

2 Scalability in Real-World Agricultural Settings: The effectiveness of AI models revealed through this study under experimental conditions must adapt to operate at bigger scales within actual agricultural fields. For instance: Data Variability: The model faces execution issues because it must adapt to environmental conditions which show major deviations from the training data collection. The model's generalizability along with its robustness depends on obtaining diverse datasets that span different geographical locations. Infrastructure Requirements: The implementation of AI systems in rural areas faces two principal obstacles which are insufficient computing power and inaccessible reliable internet connections. AI models that operate on low-cost electronic devices including smartphones and edge applications will serve as a requirement for extensive mass adoption. Farmer Training and Adoption: AI-based tool implementation needs farmers and agricultural staff to receive education about proper tool usage. Training programs and user-friendly interfaces must exist as the main keys to guarantee accessibility and adoption.

4.2 Sustainability and Environmental Benefits

The AI model boosts sustainable farming through precise fungicide management that both decreases water-carried chemicals into the environment and diminishes ecological contamination. The AI system observes present data to determine disease levels and selects specific fungicides that minimizes exposure to chemicals and safeguards environmental balance. The research findings match previous observations from Geherad and Amina (2014) who established that specific fungicide dosage leads to improved plant health with elevated nutrient content particularly protein levels in crops.

5. Conclusions

The agricultural sector uses Artificial Intelligence (AI) as a modern instrument that brings both innovative solutions and advanced approaches for disease identification throughout plant disease management systems. AI uses machine learning algorithms to identify plant diseases precisely which leads to better intervention decisions that cut down the necessity of chemical treatments. The research examined chemical inducer antifungal effects along with biological resistance mechanisms and AI-based disease management approaches to fight Botrytis fabae (B. fabae) with a reference to regular pesticidal treatment methods. The study results showed that fungal growth inhibition became more efficient with rising chemical inducer concentrations and biological agents showed equal importance in reducing infections. The AI methods delivered exceptional results because they performed better at disease identification and fungicide planning optimization. The implementation of AI-driven fungicide distribution methods resulted in a 63% decline of disease intensity which exceeded the 57% decrease rate recorded through regular procedures.

The AI system precisely determines chemical application points which enables both effective disease control and minimizes spraying that is not needed. The AI model led to both a decrease in fungicide usage by 35 percent and higher yield levels by 8 percent while cutting down costs by 12 percent which confirms its value in disease management. The AI model works as an auxiliary tool apart from stand-alone traditional methods because it helps maximize fungicide efficiency to minimize adverse effects on the environment and enhance sustainability. Cloud-based AI systems face limitations when applied to disease management though they deliver multiple benefits. The main obstacle is obtaining high-quality data necessary for making correct predictions. Artificial Intelligence models operate less efficiently under changing environmental factors including lighting levels and humidity and temperature conditions. The deep learning Convolutional Neural Networks (CNNs) face interpretability challenges that slow down adoption by farmers as well as agronomists because of their unclear algorithm behaviour. Additionally, the scalability of AI solutions in real-world agricultural settings is constrained by infrastructure limitations, particularly in rural areas with limited access to computational resources or reliable internet connectivity.

5.1 Future Research Directions

Future research should direct efforts toward improving AI disease management by focusing on the following points:

1 Integrating Remote Sensing Data: The inclusion of remote sensing technology data originating from drones or satellites and other aerial capturing devices allows disease pattern detection across broad landscape areas with better crop health assessment by the model.

2 Developing Multi-Modal AI Approaches: Future development of multi-modal AI systems through

uniting image-based analysis with soil quality data and weather information besides plant physiology information will favor creation of advanced disease prediction models.

3 Improving Model Interpretability: The investigation of explainable AI (XAI) methods should aim to enhance the transparency of AI models for farmers and agricultural stakeholders to receive user-friendly and more trusted machine learning recommendations.

4 Enhancing Scalability: These technologies will reach more farmers because the development of lean AI systems for working on basic equipment including smartphones and edge devices expands their accessibility to farmers in limited-resource regions.

The research shows that AI works together with established agricultural techniques to attain exact disease treatment and better harvest results and lower running expenses while protecting the environment. For AI to become successful in actual agricultural deployments it needs additional capabilities development along with strengthening its limitations. Full implementation of sustainable and efficient crop disease management through AI needs ongoing innovation and joint work between research teams and technicians along with agricultural professionals.

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