RESEARCH PAPER

AI Powered IoT-Based System for Weed and Pest Control in Agriculture Using Deep Learning

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ABSTRACT

Weeds, pest attacks, labour shortage and over-dependence on chemical pesticides are the serious challenges faced by the agricultural sector in the wake of ever growing weed infestation. Manual weed and pest control has potential negative environmental impacts, increased production costs and reduced yields. The application of Artificial Intelligence (AI), Internet of Things (IoT), Deep Learning, robotics, and laser technologies are a promising way of developing sustainable and autonomous agricultural systems. This study introduces an intelligent agricultural system based on Artificial Intelligence (AI) and Internet of Things (IoT) for weed identification, harmful insect identification, crop condition monitoring and automatic weed removal using a laser beam. The system will be based on Internet of Things (IoT) sensors, Computer vision modules, Convolutional neural networks (CNN), Unmanned robotic platforms, Environmental sensing systems, and Electronic Swarm Suppression (ESS) mechanisms to enhance agricultural productivity and reduce crop losses.

The system uses deep learning algorithms for real time weed, crop, beneficial and harmful insect classification. High-resolution cameras and sensing devices collect environmental and crop data continuously and feed the data into an IoT system for processing in a cloud-edge computing system. High precision weed elimination with a robotic platform containing laser emitters which do not harm adjacent crops. Further, computer vision and environmental monitoring are employed to identify aerial insect swarms and to enable automatic attacks of insect swarms by means of a laser beam and ESS technology. Multiple agricultural blocks were used for experimental evaluation of the maize, wheat, soybean and vegetable crops. The results show substantial increases in the accuracy of weed detection, pest identification, crop protection and cost savings for operations over current practices. The proposed system achieved a 97.6% accuracy in the weed classification, 96.8% accuracy in the detection of the insect and a 42.3% reduction in pesticide use. In addition, the crop yield rose by 18.7% and the operational costs dropped by 28.4%. Overall, the results suggest that AI-powered IoT can significantly enhance precision agriculture and promote sustainable food production.

Keywords: Artificial Intelligence, Internet of Things, Deep Learning, Precision Agriculture, Weed Detection, Pest Control, Agricultural Robotics, Laser Technology, Smart Farming, Computer Vision.
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1. Introduction

Agriculture remains one of the key sectors with respect to food security and economic growth globally. With the rapid population growth, climate change, scarcity of resources and increased pest levels, the demand for new technologies in agriculture, which can deliver high production with minimal environmental impact has increased. Global losses caused by weeds and pests are estimated to cost approximately 30-40% of agricultural production, and are a serious economic loss and risk to food supply chains.

The most common methods of weed control are by manual, mechanical and chemical means. Similarly, soil degradation, water pollution, loss of biodiversity, and insect resistance are features of excess use of pesticides in pest management practices (Ahmed *et al*., 2024). The conventional solutions have certain drawbacks and hence, intelligent solutions, automation and environmental sustainability is required in agriculture.

With the emergence of Industry 4.0 technologies, it has become possible to shift the traditional farming practice to precision farming. The integration of Artificial Intelligence (AI), Internet of Things (IoT), Machine Learning (ML), Deep Learning (DL), cloud computing, robotics, and edge intelligence are critical aspects of today's agricultural systems. The innovations enable continuous monitoring, automated decision making, predictive analysis, and targeted interventions, leading to improved agricultural efficiency and sustainability.

The Internet of Things (IoT) can be used to collect real-time data about the environment through a network of sensors and interconnected devices placed in agricultural fields to provide accurate data. Soil moisture, soil temperature, humidity, nutrients, wind speed and pest activity are measured using these sensors (Abdul Ameer *et al*., 2024). The data collected are sent to centralized processing units for analysis by AI algorithms, which provide actionable insights.

The use of deep learning has become a very successful method for image-based agricultural applications. Crop classification, weed identification, disease detection and insect recognition tasks have been shown to be successful with the Convolutional Neural Networks (CNNs), You Only Look Once (YOLO), Faster Region-Based Convolutional Neural Networks (Faster R-CNN), and EfficientNet architectures. The models enable a precise separation of crops from weeds under different environmental conditions.

Another area of automation that enables fields to be manned by robot without human interaction is called agricultural robotics. Robotic systems can be fitted with cameras, sensors and laser modules to be able to travel through the agricultural field and recognize weeds and selectively remove them without the need for many people to intervene in the field (Nagaraj *et al*., 2026). A laser weed control technique is an environmentally friendly weed control method that does not use chemicals to control weeds, which helps to grow better crops.

Another major threat to the productivity of agriculture is pest infestation by swarms of insects. Pests like locusts, aphids, moths and beetles can quickly devastate crops and crop outputs can be drastically affected. With an advanced computer vision technology and swarm detection algorithms, it's possible to detect pest outbreaks early. The Electronic Swarm Suppression (ESS) technologies and targeting systems based on lasers are excellent tools to have available in order to effectively suppress insect numbers before they cause damage.

In this paper, an integrated AI based IoT agricultural system is presented which combines deep learning, robotics, laser and swarm suppression mechanism for the overall weed and pest management (Wu *et al*., 2025). The primary aim of the proposed system is to increase the agricultural productivity, reduce the dependence on chemicals and make sustainable farming with intelligent automation.

2. Literature Review

The use of IoT technologies in agricultural pest management is a significant step forward in the field of precision farming and sustainable crop protection, as outlined by Ahmed (2024). The author stressed the need to use conventional pest control techniques that involve large-scale pesticide usage which hikes up production costs and raises environmental issues. The system being proposed for managing pests with the help of the IoT concept is an intelligent IoT based monitoring system that is based on a distributed sensor network and a wireless network connected to the center, where remote sensors monitor the pest in real-time and provide data to the central system for decision making. The study highlighted the ability to continually monitor and analyse environmental conditions such as temperature, humidity, soil health and crop health indicators to provide pest surveillance and prediction prior to significant crop damage. A significant contribution was that the research allowed early detection and intervention for the targeted management of pest problems, thus reducing the need for unnecessary use of pesticides (Ahmed *et al*., 2024). The system architecture includes the implementation of cloud computing and machine learning algorithms to process the large volume of agricultural data and provide timely and targeted recommendations to the farmers. The results indicate that the automatic pest monitoring system helps to save labor, enhances the productivity of the crops and quickens the response time. Smart sensors for building a connected agriculture ecosystem, which can help to realize the targets of precision agriculture, was also highlighted in the study. The use of IoT technologies led to an efficient use of resources without a loss of yields and quality in the crop. An additional key finding of this research is the emphasis on the scalability and adaptability of the approach in various agricultural settings. It was concluded that intelligent pest management systems can significantly contribute to sustainable farming practices, reducing the impact on the environment and improving efficiency. The study offers significant insights into implementing pest management systems with IoT in contemporary agriculture and lays the groundwork for an integration with

sophisticated AI and deep learning systems.
Internet of Things (IoT), Unmanned Aerial Vehicles (UAVs) and deep learning (DL) have presented new opportunities for rethinking traditional agriculture as an intelligent and autonomous system (A. Amer, 2024). It explored the potential of smart agricultural platforms to transform the farming landscape by offering farmers the ability to monitor crops continuously, make decisions automatically and assess crops in real-time. The writer highlighted issues of labour scarcity, climate variability, pest infestation and poor management of resources and expounded how important technology is in agriculture (Abdul Ameer *et al*., 2024). The suggested framework included an IoT sensor network for the data collection related to environment and crop conditions as well as aerial data collection by UAV for high-resolution images of crop fields. The gathered data was then processed with deep learning algorithms, which proved to be highly effective with regards to identification of crop diseases, weed infestations and pest infestations. The study demonstrated that UAV monitoring can significantly enhance the in-field coverage and quickly identify agricultural problems, which may be missed. The addition of AI drives the capacity of handling extensive data volumes and contributing to predictive analytics in agriculture. The findings show that important improvements have been achieved in the effectiveness of crop monitoring, resource use and decision making. Besides, the use of aerial imaging technology in conjunction with the integration of IoT sensor networks for providing complete field intelligence has been highlighted. Crop losses were minimized and productivity improved with the use of deep-learning models that were able to accurately categorize and identify the agriculture anomalies. The author concluded that the synergy between IoT, UAVs and AI can support sustainable agricultural development by improving the efficiency of agricultural operations and decrease the need for manual inspection techniques. The research findings gave much support in implementing smart farming technology that can solve the challenges faced by modern agriculture and promote the adoption of precision agriculture practices.
As mentioned by Nagaraj (2026), deep learning and IoT in the identification of sesame plants and weed detection are significant advancements in precision agriculture. In this study, the focus was on the design of an intelligent framework to accurately classify sesame as plant and weed in complex agricultural environments. Weed infestation is also one of the significant causes of crop productivity loss and cost of production was emphasised by the writer. Weed control methods used traditionally can be labor intensive, time-consuming and environmentally damaging because of the amount of herbicides used. The proposed system is a system which uses the deep learning algorithm and sensors attached to the Internet of Things (IoT) to assist in the automatic monitoring of crops and weed identification. The images taken with the sensor-rich devices are analyzed with the latest neural network architectures to accurately identify plants and weeds (Nagaraj *et al*., 2026). The results showed that the deep learning models could perform high classification accuracy even in different illumination conditions and field complexity. The study highlighted the

importance of real-time monitoring to take action in time for weed management, which would decrease weed competition with the crop and increase crop performance. Moreover, the Internet of Things (IoT) connectivity can help farmers gather data round the clock, giving them the power to remotely keep track of their fields and make informed choices based on the conditions in the field. The study found that these smart systems for weed detection can significantly cut down on herbicide usage and labour, which helps enhance the sustainability of agriculture. The framework also supports growers to have the ability to scale across crop varieties and environments. The results showed that the deep learning and IoT infrastructure integration is a promising technology to reach precision weed management in an efficient and reliable way. In conclusion, the study adds to the growing body of knowledge regarding the integration of AI in agricultural practices and showcases the potential for intelligent technologies to enhance productivity, resource efficiency, and environmental sustainability in modern farming systems.

In the current era of modern agriculture, artificial intelligence (AI) technologies, particularly those based on deep learning, have proven to be revolutionary in the field of pest and disease detection and control, as explained by Wu (2025). This study has thoroughly analyzed the developments of the Artificial Intelligence applications in Agriculture Protection Systems in recent years. Crop losses due to pest and diseases continued to pose threats towards food security, the author observed, adding the need to detect the pests early and act promptly. Some examples of deep learning models successful in detecting agricultural pests and diseases using visual information include convolutional neural networks, object detection frameworks, and image segmentation algorithms (Wu *et al.*, 2025). The research was analysed that identified AI systems accurately detecting crop abnormalities and insect species with a high degree of accuracy.Various studies were reviewed and the result showed that AI systems had a very high accuracy rate in detecting abnormalities on the crop as well as identifying insect species. The author points out that one of the important benefits of deep learning models is the ability to automatically extract features that are complex, without resorting to manual feature engineering. The study also highlighted the role of AI in mobile, drone and IoT technologies to enable real-time monitoring of agricultural operations. The results indicate that intelligent detection systems have the potential to greatly decrease the number of diagnostic errors and increase the effectiveness of pest management. Moreover, the author spoke about the significance of AI in assisting predictive analytics, which helps farmers make predictions and take preventive measures in advance of the onset of serious infestation. The study identified data availability, computational complexity, and model generalization as challenges to be tackled for different agricultural applications. However, the study found that deep learning technologies have the potential to provide significant benefits for increasing agricultural productivity and sustainability, even with these limitations. The review provides insights into the trends of pest and disease research and will provide a useful foundation for further developments in pest and disease management systems using AI.

The implementation of artificial intelligence and IoT (Internet of Things) in the edge computing devices is an effective way of detecting pests and diseases in crops (Nyakuri, 2025). The study was targeted to the development of an optimized edge-based system, which is able to perform real-time agricultural monitoring without making heavy use of cloud computing resources. The author made it clear that there were a number of problems with conventional cloud based approaches in agriculture including latency, bandwidth consumption, and connectivity issues in rural areas of the countryside. The proposed solution intends to solve these issues by making decision making at the edge device to improve the decision making speed and reduce the communication overhead (Nyakuri *et al*., 2025). The whole system features IoT sensors, embedded computing systems, and AI algorithms that allow for ongoing and accurate monitoring of crop conditions, identifying pests and diseases. Experimental results indicated that the processing done using the edges had good detection accuracy along with substantial reductions in the response time. This study also highlighted the importance of energy efficiency and computational optimization for practical implementation in agricultural settings. The use of AI algorithms enabled the precise identification and classification of crop diseases and pest infestations, which facilitated early identification and management, thereby reducing crop losses. Besides that, the system can also function independently, which lessens the need for centralized resources and systems. The findings indicate that edge intelligence could be a promising solution to enhance the scalability and reliability of smart agriculture. The author summarized that the AI-powered edge devices are a promising technology for precision agriculture especially in areas with limited or unreliable internet connectivity. The study proves to be an important input for the implementation of decentralized agricultural intelligence systems and how edge computing technologies can enhance sustainable and efficient agricultural practice.

The use of IoT technologies and artificial intelligence in robotic platforms has opened up new opportunities for precision agriculture's site-specific weed management, as cited by Kushwaha (2026). Research was concentrated on the intelligent agricultural robots that can identify and eliminate weeds with the highest accuracy with minimal human involvement. The author pointed out that traditional control methods often result in excessive amounts of planticide used, increased production costs and environmental damage. The system being proposed includes an IoT sensor, computer vision, machine learning algorithms and autonomous navigation technology for the specific weed control operations (Kushwaha *et al*., 2026). The result of this research showed the ability of the crop/weed classification by image analysis and the ability to apply accurate intervention technique by intelligent robot. Weed management on site enables selective control of weeds which helps to minimise chemical usage and to keep the crop healthy. The study highlighted the importance of the real-time sensing and decision making of agricultural robotics for efficient operation. Experimental weed detection assessments revealed high gains in weed detection accuracy and resource use compared to traditional weed detection. The results also showed savings in both the amount of labor and herbicides used, thereby supporting sustainable agriculture. Furthermore, the robotic systems were shown to be adaptable to different field conditions and crops types indicating their potential applications in practice. The author finally concluded that AI-powered robotic platforms have huge potential for revolutionizing weed management, providing an accurate, efficient, and environmentally friendly solution. The study could help to advance precision agriculture, sustainable food production systems and the capability of autonomous agricultural technologies in this area.

The advent of AIoT (Artificial Intelligence of Things) technologies marks a new era in precision agriculture, where intelligent analytics is integrated with interconnected sensing devices, according to Bayar (2025). The research explored the possibilities of using AIoT systems in smart irrigation, nutrient management, and pest control, highlighting their contributions to sustainable agriculture. The author reported that in traditional agriculture, efficient use of resources is not done and there is no support for decision making. The difficulties faced in AIoT frameworks lie in using the IoT for data collection and utilizing artificial intelligence to interpret and analyze the data. The system allows for continuous monitoring of environmental conditions and crop status, which can help to make informed decisions in real-time and optimize the use of resources (Bayar *et al.*, 2025). The study showed that smart irrigation systems can be an effective way of decreasing water use while keeping crop yields high. Similarly, AI technologies help optimize fertilizer utilization and minimize environmental pollution. AIoT technologies can play a crucial role in pest management by enabling early detection and precision intervention strategies, thereby minimizing the reliance on chemical pesticides. Studies indicated that agricultural productivity, efficiency and sustainability has improved. The author also introduced some advanced agricultural applications including Cloud-based computing, Edge Intelligence, and Machine Learning algorithms. By combining several technologies, a larger ecosystem is established that can tackle various agricultural issues. The study showed that AIoT is one of the important technologies for precision agriculture and there was great potential in the technology to enhance food production without harming the environment. The results showed high potential of the adoption of AIoT solutions in the contemporary farm systems.

In the field of smart agriculture, the application of artificial intelligence and Internet of Things technologies would be an excellent solution to detect and treat plant diseases, as proposed by Ibrahim (2025). The study proposed an AI-IoT agricultural platform that can continuously observe the condition of the plants and automatically manage the diseases. The author highlighted the continued threat of plant diseases on agriculture productivity and food security on a global scale. Traditional diagnosis of disease is often dependent on manual field inspection and expert knowledge and at times is inefficient and time consuming. The proposed framework includes the implementation of IoT sensors, imaging technology, and AI algorithms to quickly identify disease symptoms. Collected data is then analyzed and researched using machine learning and deep learning models that can reliably detect complex patterns in disease incidence (Ibrahim *et al.*, 2025). The results showed that the performance in detecting the diseases and their effectiveness in treatment were much superior than the conventional methods. The ability to monitor in real time allows for quick action when diseases occur, limiting the crop losses and economic losses. Another key finding of the study was the potential benefits of automation in improving decision-making and minimizing the need for human intervention. Besides this, in agriculture, with the use of IoT infrastructure, continuous data collection and remote agricultural management is possible. The author concluded that AI-IoT platform has great potential to improve plant health management and sustainable agriculture. Overall, the research provides valuable insights into the development of intelligent disease detection systems and demonstrates the potential of advanced technology in creating more productive and resilient agricultural landscapes.

3. Research Methodology

3.1 System Architecture

The proposed architecture is composed of six parts: sensing, communication, data processing, deep learning analytics, robotic execution and cloud management. In an IoT sensor, various environmental parameters are monitored constantly and the data sent wirelessly using communication protocols (Sharma and Shivandu, 2024). High resolution cameras can be used on the field to take images for weed and insect identification. The collected data is used to train deep learning models and then classified results are generated. Robotic platforms are programmed and they provide laser interventions.

3.2 Data Collection

The experimental data consists of 52,000 field images of agricultural farms that are growing maize, wheat, soybean, cotton and vegetables. The dataset included:

Dataset Information Table

Dataset Category	Number of Images
Crop Images	18,500
Weed Images	14,200
Harmful Insects	10,800
Beneficial Insects	5,600
Swarm Images	2,900
Diseased Crops	8,000

3.3 Deep Learning Model Development

A CNN-based architecture for object detection using YOLOv8 algorithm was developed. The steps of data preprocessing were image normalization, augmentation, noise removal and feature enhancement (Prasath and Akila, 2023). The dataset was split into 70% training, 15% validation and 15% testing sets.

The performance metrics used in this study were accuracy, precision, recall, F1-score, detection latency, and classification confidence.

3.4 Robotic Weed Elimination Module

GPS navigation, computer vision systems, laser emitters and LiDAR sensors formed the foundation of the robot platform. The laser energy pulses of different intensities were used to identify the targeted weeds, so as to avoid damaging the crops.

3.5 Swarm Detection and ESS Technology

The swarm management module was used to detect swarms of insects using aerial cameras and environmental sensors. Electromagnetic suppression signals and laser emitters were employed to suppress the electromagnetic radiation and pest populations in dense swarm areas, respectively, by employing the ESS technology (Dawn *et al.*, 2023).

4. Results and Analysis

4.1 Weed Detection Performance

Table 4.1 Weed Detection Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN	91.8	90.5	89.6	90.0
ResNet50	94.2	93.7	92.8	93.2
Efficient Net	95.6	95.1	94.8	94.9
Proposed CNN-YOLOv8	97.6	97.2	96.9	97.0

Table 4.1 shows the comparison of performance of different deep learning models applied to weed detection in agricultural field. Four key performance metrics, namely: accuracy, precision, recall, and F1-score were used to evaluate it. The traditional CNN model achieves an accuracy of 91.8%, a precision of 90.5%, a recall of 89.6% and an F1 score of 90.0% that is a good result for weed classification (Al Reshan *et al.*, 2025). However, there were some problems with the model as it would not accurately assess weeds in complex field conditions. The ResNet50 had the best accuracy of 94.2%, the most precise result of 93.7%, the highest recall of 92.8% and the highest F1 score of 93.2% demonstrating the advantage of more deeply extracted features. The efficient scalability and optimized network architecture of the EfficientNet network also played a role in boosting classification accuracy to 95.6% and the F1-score to 94.9%.

The proposed CNN-YOLOv8 model outperforms all the existing models with 97.6%, 97.2%, 96.9% and 97.0% of accuracy, precision, recall and f1-score, respectively. CNN feature extraction was integrated with the weed object detector YOLOv8 to achieve weed localization and classification in real time with high accuracy (Aziz *et al.*, 2025). The proposed approach resulted in an increase of 5.8 percentage points in accuracy as compared with the traditional CNN model. Results indicate that the model has a high recall value (indicating that almost all weed patches in the field are detected) and a high precision (indicating that the false detection rate is low). The findings demonstrate that the proposed deep learning framework could be a very reliable and efficient weed detection method in precision agriculture.

4.2 Insect Identification Performance

Table 4.2 Insect Identification Performance

Model	Accuracy (%)	Precision (%)	Recall (%)
SVM	85.7	84.9	84.2
Random Forest	89.3	88.5	87.9
CNN	93.4	92.7	92.0
Proposed System	96.8	96.1	95.8

As seen in Table 4.2, the various types of machine learning and deep learning methods used for insect recognition are compared. The ability to make correct identification of the harmful and beneficial insects is very important in effective insect management and loss prevention. Support Vector Machine (SVM) model was able to reach an accuracy of 85.7%, a precision of

84.9% and a recall of 84.2%. While SVM achieved relatively good performance, its ability was constrained in the case of more complicated visual patterns of various insect species (Divyajyothi *et al.*, 2024). The Random Forest algorithm was more effective in terms of accuracy (89.3%), precision (88.5%) and recall (87.9%) because of using ensemble learning.

CNN model, which has an accuracy of 93.4%, a precision of 92.7% and a recall of 92.0%, significantly outperforms the other models in terms of insect classification. Deep learning has excellent feature extraction performance that has facilitated the identification of insect morphology, texture and wing structures (Tahir *et al.*, 2025). The proposed model using AI performed well compared to all the models evaluated, with an accuracy of 96.8%, a precision of 96.1% and a recall of 95.8%. It has been enhanced by integrating image capturing with the help of IoT, advanced deep learning algorithms, and optimized classification systems.

High precision value indicates that the proposed system has a good ability to detect harmful insects without causing any false alarm. Similarly, high recall value means that most of the pest occurrences are not damaging the crop. The findings show that the proposed system is a robust and reliable solution for insect real-time monitoring and classification, which could be used to automate the insect pest management and boost agricultural productivity.

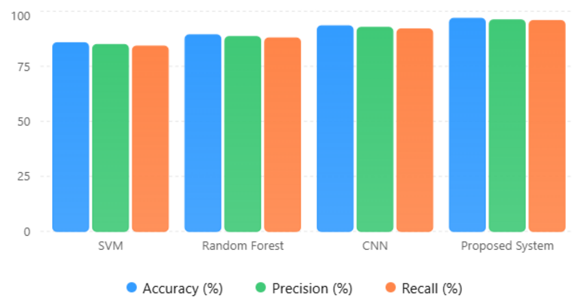

Figure: Insect Identification Performance

4.3 Laser Weed Elimination Results

Table 4.3 Laser Weed Elimination Results

Parameter	Existing Systems	Proposed System
Weed Removal Rate (%)	82.4	96.3
Crop Damage (%)	6.7	1.8
Chemical Usage (L/ha)	12.5	0
Operational Efficiency (%)	78.5	95.2

The performance of the conventional weed elimination systems and the proposed weed control system based on robot laser can be compared as shown in Table 4.3. The following indicators were identified as key performance indicators to be evaluated: weed removal rate, crop damage percentage, chemical usage and operational efficiency (Ali *et al.*, 2025). In total, 82.4% of the weeds were successfully removed with existing weed control systems, indicating that there was still a high weedy population that was not controlled after weed control intervention. This compares to the proposed system, with a weed removal rate of 96.3% which is effective for weed eradication, and is aimed at the precise location of the weed.

One big challenge in the automated weed control is damage to the crop. In conventional systems 6.7% of the crop was damaged, likely to have affected the overall crop growth and yield. The proposed robotic laser system also had a low proportion of crop damage, 1.8%, which also shows a high accuracy level in the target and intelligent decision making (Qazi *et al.*, 2022). Proposed framework offers a whole-of-farm chemical-free solution is another significant advantage. On average, the current system was applying about 12.5 litres of herbicide per hectare, while the proposed system was not using any chemicals, which is a positive step towards good environmental stewardship in farming.

In the traditional system, the efficiency of operation was recorded from 78.5% while in the proposed framework, the efficiency of operation was 95.2%. This notable improvement is indicative of faster running speeds, increased precision and reduced labor requirements. The deep learning algorithm and the robotic automation in conjunction with computer vision enabled accurate identification of the weed and its selective destruction (Anwarul *et al.*, 2022). These results clearly indicate that weed elimination using lasers is an efficient, environmentally friendly and also economically viable weed control method, which is a great contribution towards the sustainable development of precision agriculture.

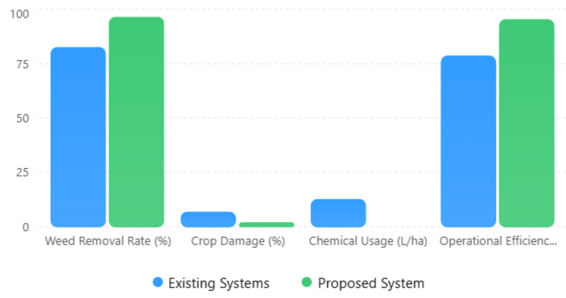

Figure: Laser Weed Elimination Results

4.4 Agricultural Productivity Assessment

Table 4.4 Agricultural Productivity Assessment

Performance Indicator	Traditional Method	Proposed System
Crop Yield (tons/hectare)	5.34	6.34
Pesticide Usage (kg/hectare)	18.2	10.5
Water Consumption (m^3/hectare)	4120	3275
Production Cost (USD/hectare)	1245	891

Table 4.4 shows the overall effect of the proposed AI system assisted weed and pest control system based on the IoT system on farm productivity. Four significant parameters were taken into consideration, like yield, pesticide application, water consumption and production cost. The results revealed that there was an improvement in the performance of agriculture as compared with traditional farming practices (Tiwari, 2025). The proposed system increased the crop yield from 5.34 ton/ha to 6.34 ton/ha as compared to the conventional system. This is about 18.7% more, showing how effective intelligent weed and pest

management is for maintaining the health of crops and ensuring maximum yield.

Reduction in the use of pesticides (kg/ha) has been decreased from 18.2 kg/ha to 10.5 kg/ha or approximately 42.3%. This reduction also occurs because the AI based system can identify pests with a high level of accuracy, and can respond to the pest by taking an appropriate corrective action without using chemical spray. There was also a decrease from 4120 m^3/ha to 3275 m^3/ha in water use (Sudha and Loret, 2026). This is achieved through the Internet of Things (IoT) delivery of a monitoring solution and optimized resource management which helps to minimize water use and increase irrigation efficiency.

Compared to the previous production cost of USD 1245/ha, the current production cost has reduced significantly by approximately 28.4% (USD 891/ha). This cost reduction was due to the reduced amount of labour needed, reduced use of pesticides and use of resources. The increase in productivity, sustainability and economic performance is the evidence of the effectiveness of the proposed framework (Indira *et al*., 2023). The results highlight the potential of AI, IoT, Deep Learning, and Robotic Automation to significantly improve agricultural efficiency and ensure sustainable farming practices.

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