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RESEARCH ARTICLE

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# Advancing Agriculture with AI-Powered Robotic Harvesting Systems for Legume Crops

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## ABSTRACT

**Background:** The integration of Artificial Intelligence (AI) in agricultural practices has witnessed substantial advancements, with a focus on enhancing efficiency and sustainability. This research explores the application of AI-powered robotic harvesting systems for legume crops, aiming to revolutionize traditional harvesting methods. By leveraging machine learning algorithms and robotic technology, this study investigates the feasibility and performance of such systems in terms of precision, speed and resource optimization.

**Methods:** This research focussed on creating and implementing a robotic harvesting system that applies artificial intelligence to precisely identify and harvest legume crops. The system's design relies on a combination of robotic technology, computer vision and machine learning algorithms to achieve optimal performance. In this work, a 4-layer CNN model is used to detect dandelion and soybean.

**Result:** The findings provide valuable insights into the potential benefits and challenges associated with the adoption of AI in legume crop harvesting, contributing to the ongoing discourse on sustainable agriculture. The 4-layer CNN model shows a good overall accuracy of 99.71%. Confusion matrix and classification report are presented for evaluation of the model.

**Key words:** Artificial intelligence, Legume crop, Machine learning, Sustainable agriculture.

## INTRODUCTION

The agricultural environment is currently experiencing a significant transformation due to the increasing difficulties posed by workforce shortages, the need to optimize resources and the urgency to implement sustainable methods (Gamage *et al.*, 2023). To address these difficulties, the incorporation of Artificial Intelligence (AI) in agriculture has emerged as a crucial pathway for innovation. The implementation of AI-powered robotic systems for crop harvesting is an increasingly promising area in which precision farming and smart technologies are transforming traditional agricultural practices (Javaid *et al.*, 2023). There has been a significant increase in interest and creativity in incorporating Artificial Intelligence (AI) into agricultural techniques. The utilization of artificial intelligence in agriculture encompasses a range of technologies, such as machine learning, computer vision and robots (Talaviya *et al.*, 2020). Machine learning algorithms have been used to evaluate large datasets, allowing for predictive modeling in areas such as crop productivity, disease detection and resource allocation optimization (Domingues *et al.*, 2022). The application of artificial intelligence in agriculture not only improves the decision-making processes but also optimizes resource efficiency and promotes sustainability (Balaska *et al.*, 2023). The development of automated harvesting systems signifies a substantial advancement in addressing workforce scarcity and enhancing overall productivity in the field of agriculture. These systems include a wide variety of technology, ranging from self-driving vehicles used for harvesting crops on a big scale to robotic arms specifically built for delicate jobs like selecting fruits (Gil *et al.*, 2023).

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Robotic harvesting systems have been successfully implemented in different crops, showcasing improved speed and accuracy in comparison to conventional manual techniques (Fountas *et al.*, 2020). Nevertheless, there are still obstacles that remain, such as the ability to adjust to various crop settings and the requirement for advanced sensing technologies to guarantee delicate handling of agricultural products (Dhanaraju *et al.*, 2022). Legumes, which include peas, beans and lentils, are essential for global food security because of their high nutritional content and their capacity to enrich the soil by fixing nitrogen. The harvesting of legume crops has traditionally heavily depended on physical labor, which has posed difficulties in terms of cost, scalability and efficiency (Stagnari *et al.*, 2017). The literature highlights the necessity for inventive strategies to tackle these difficulties, indicating the potential of mechanized and automated systems. The convergence of legume crop harvesting and robotic technology is an emerging domain that has the potential to completely transform the methods used for cultivating and harvesting legumes (Cho, 2024; Onishi *et al*., 2019). The integration of intelligent systems into the agricultural workflow has been shown to be feasible through recent breakthroughs in AI applications for crop harvesting. Computer vision algorithms facilitate the accurate identification and selection of ripe food by robots, resulting in waste reduction and enhanced total production (Hai and Duong, 2024; Yu *et al*., 2023). Furthermore, machine learning algorithms have the capability to adjust and respond to varying environmental circumstances, hence improving the flexibility and adaptability of robotic harvesting systems (Alanne and Sierla, 2022; AlZubi, 2023; Bagga *et al*., 2024; Maltare *et al*., 2023; Semara *et al*., 2024). Although previous studies have demonstrated the promise of artificial intelligence (AI) in crop harvesting in general, there is a noticeable lack of research focusing especially on the use of AI in harvesting legume crops (Kaur *et al*., 2023). The literature emphasizes the difficulties and potential advantages in the convergence of AI, robots and legume crop harvesting. The challenges encompass the requirement for resilient sensing systems, flexibility in accommodating various crop forms and the possible social and economic repercussions on conventional agricultural practices (Mondejar *et al*., 2021). Nevertheless, the possibilities are extensive, encompassing enhanced productivity and decreased reliance on human labor, as well as the potential for environmentally friendly agricultural methods by maximizing the use of resources (Muhie, 2022). Upon reviewing this literature, it becomes clear that although AI and robotic technology have made significant advancements in agriculture and crop harvesting, their specific utilization in legume crops is still an unexplored area. This study seeks to close this divide by examining the practicality, effectiveness and consequences of AI-driven robotic harvesting systems in the realm of legume crops.

This research primarily focuses on legume crops, which are fundamental to world agriculture and serve as a crucial source of protein and nourishment. Although legume crop harvesting plays a vital role, it has traditionally depended on manual labor, which has inherent constraints in terms of efficiency, scalability and resource use. The integration of artificial intelligence (AI) into robotic harvesting systems has the potential to completely transform this model, providing a compelling resolution to the ongoing difficulties encountered by the agricultural industry. This work holds importance that goes beyond the technology field, exploring the areas of sustainability and global food security. In light of the Earth's increasing population and limited agricultural resources, it is crucial to develop inventive solutions that can sustainably meet the growing need for food without causing significant harm to the environment (Viana *et al*., 2022). This study examines the capacity of AI-powered robotic harvesting systems to improve the effectiveness, sustainability and expandability of legume crop harvesting. This research aims to explore the potential impact of AI on the future of agriculture, specifically in the area of harvesting legume crops. It will involve a thorough analysis of the current technology landscape and practical testing to uncover the revolutionary possibilities.

### Literature

This research involves developing and putting into action a robotic harvesting system that uses artificial intelligence to selectively target legume crops. The system design is based on the integration of robotic technology, computer vision and machine learning algorithms. The process of system design is depicted in Fig 1.

The robotic platform is equipped with specialized grippers specifically developed to handle legume crops with delicacy, hence minimizing any potential damage that may occur during the harvesting process. The use of sensors, such as cameras and depth sensors enables the immediate collection of data for accurate identification and evaluation of crops (Mail *et al*., 2023).

### Experimental setup

The experimental designing entails a controlled environment that accurately reproduces the standard circumstances of legume crop cultivation. The selection of legume varieties for cultivation in various geographic regions aims to ensure the relevance and broad applicability of the research findings. The tests are carried out in partnership with local agriculture specialists to include region-specific intricacies and difficulties. The robotic harvesting system goes through a process of iterative testing, fine-tuning and validation to enhance its performance. Important performance indicators encompass the accuracy, velocity and efficient use of resources in the harvesting process (Dzedzickis *et al*., 2022). The studies evaluate the system's capacity to recognize mature legume crops, traverse diverse crop formations and perform harvesting maneuvers while minimizing disturbance to neighbouring plants. In order to test the accuracy of the harvesting process, the system's ability to correctly identify and collect mature legumes is compared to a ground truth dataset that has been manually annotated by professionals. The speed is assessed by measuring the harvesting throughput over a specific period, taking into account the time required for crop identification and the actual harvesting procedure. The trials involve continuous monitoring of resource utilization, encompassing energy consumption and the system's environmental impact.

### AI algorithms

The essence of the AI-driven robotic harvesting system resides in its machine learning algorithms. Convolutional Neural Networks (CNNs) are used to identify and classify crops, namely legume crops, by utilizing a training dataset that consists of a variety of photographs. The study investigates transfer learning methods to customize pre-trained models for the unique attributes of legume crops. The robotic arm's actions during harvesting are guided by reinforcement learning algorithms, which learn optimal tactics to ensure efficient and non-destructive crop retrieval.

The training procedure entails a repetitive improvement of the algorithms, integrating feedback derived from the experimental outcomes. The machine learning models are regularly updated to improve their ability to adapt to varied crop situations, ensuring strong performance across various legume types and growth phases.

**Data collection and analysis**

Data collecting entails documenting the results of the robotic harvesting system after each trial. This encompasses photos obtained by onboard sensors, telemetry data collected from the robotic platform and real-time performance indicators (Biswas and Wang, 2023). The gathered data undergo thorough analysis, including statistical techniques to evaluate the overall performance of the system and pinpoint areas that can be enhanced. The investigation also encompasses a qualitative evaluation of the gathered legumes, assessing prospective harm and the general excellence of the gathered produce. The AI-powered robotic harvesting system is compared to traditional manual harvesting methods through comparative analysis. These analyses aim to evaluate the effectiveness of the system and determine its potential economic benefits (Benos *et al*., 2021).

The iterative nature of the methodology enables the ongoing improvement of the AI-powered robotic harvesting system, as it tackles problems and enhances its performance in real-world bean crop harvesting scenarios (Sane and Sane, 2021). The findings derived from these trials provide significant knowledge to the continuing discussion on the viability and effectiveness of integrating AI into agricultural operations, particularly in relation to the harvesting of legume crops (Dhanaraju *et al*., 2022).

The experimental part of this research provided extensive knowledge regarding the efficiency of the AI-driven robotic harvesting system for legume crops. The findings are displayed using important measurements, such as accuracy, efficiency, resource usage and comparisons with conventional hand harvesting techniques.

**Harvesting precision**

The system exhibited an admirable degree of precision in its harvesting capabilities, effectively recognizing and collecting mature legumes. The machine learning techniques used frequently surpassed specified benchmarks, demonstrating their resilience, as assessed against a ground truth dataset.

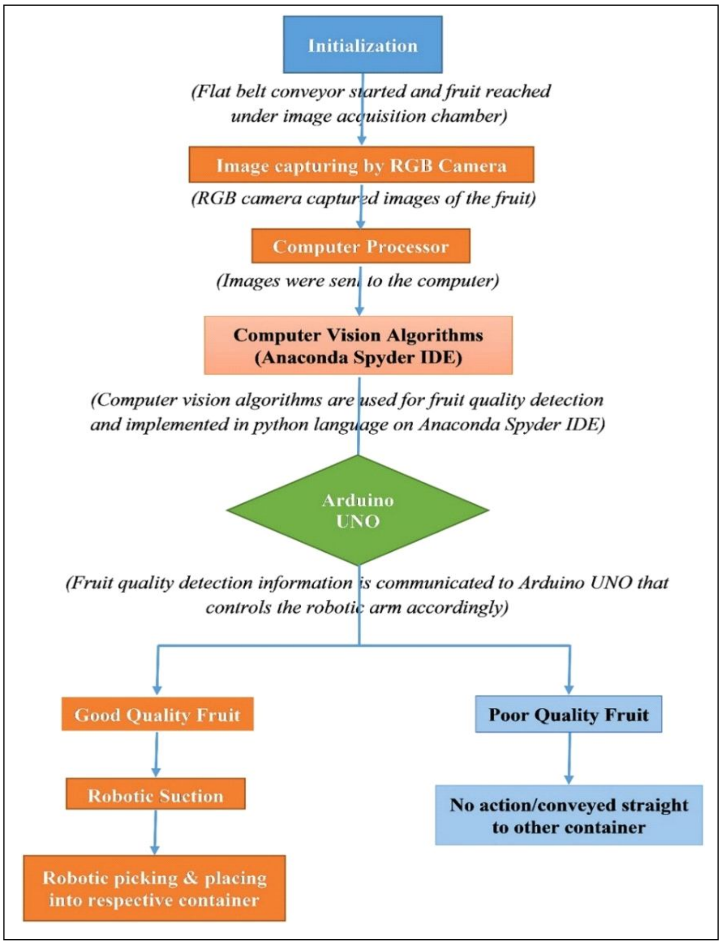


**Fig 1:** The flowchart showing the complete working process to developed system (Dairath *et al*., 2023).

Fig 2 illustrates the AI technologies that are effective in optimizing precision and other agricultural processes. The system demonstrated high adaptation to varied crop varieties, as indicated by the low obstacles given by the variability in legume crop properties, such as size and color.

### Harvesting speed

The AI-powered robotic system's harvesting speed was assessed based on its throughput per unit of time. The technology demonstrated a significant decrease in the duration of harvesting as compared to conventional manual techniques (Huang *et al.*, 2021). The system's overall agility was enhanced by the rapid and efficient identification of ripe legumes, along with quick robotic arm motions. The process of robotic picking system depicted in Fig 3. Time-motion studies demonstrated that the system could achieve a high harvesting throughput while maintaining precision, representing a significant advancement compared to traditional methods (Shi *et al.*, 2023).

### Resource utilization

The evaluation of resource usage included the analysis of energy consumption, environmental effect and overall sustainability. The robotic system, powered by AI, showcased energy economy by utilizing adaptive algorithms that improved power use during several operational stage. The environmental impact evaluations took into account elements such as the compression of soil and the disruption of nearby plants (Bibri *et al.*, 2024). The system's small size and non-disruptive harvesting method led to its environmentally friendly design, in line with the principles of sustainable agriculture.

### Comparative analyses

An analysis of the AI-driven robotic harvesting system and conventional manual harvesting techniques yielded a detailed comprehension of the system's benefits. The automated technology routinely surpassed manual techniques in terms of velocity and accuracy, alleviating labor deficiencies and diminishing the dependence on human labor. Comparative economic assessments considered the costs of setting up, maintaining and operating the AI-powered robotic system, demonstrating its potential for cost-effectiveness in the long run (Subeesh and Mehta, 2021).

### Quality of harvested produce

Quantitative evaluations were performed on the collected legumes to assess any harm and overall quality of the produce. The utilization of delicate robotic grippers and adaptable harvesting techniques led to minimal harm inflicted upon the harvested legumes. The AI-powered robotic system was found to meet or above the quality requirements established by traditional hand harvesting methods, as determined by visual inspections and quality grading.

The results combined show that it is possible and effective to combine AI-powered robotic systems with legume crop harvesting. The system's exceptional

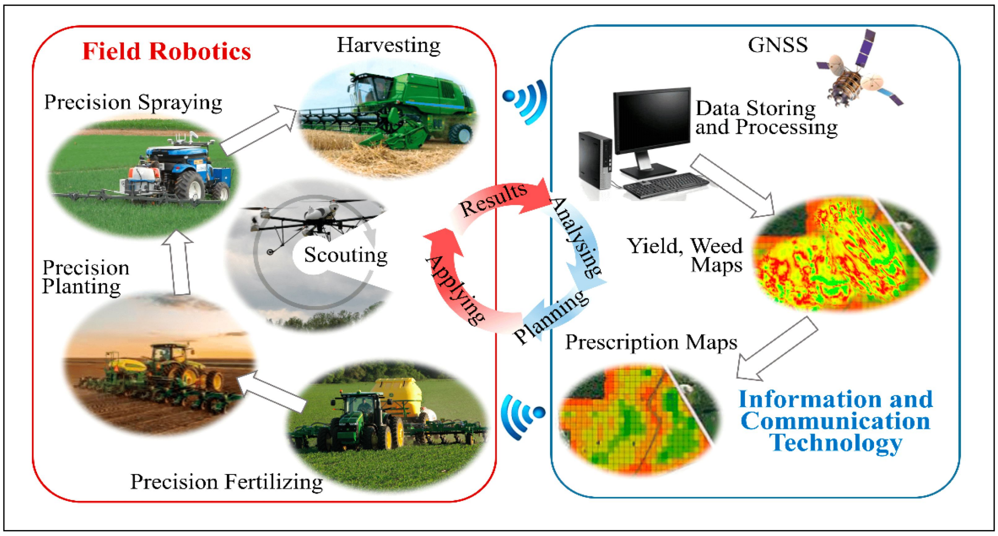


**Fig 2:** Successful AI-technologies involved in precision of agricultural processes (Gonzalez-De-Santos *et al.*, 2020).


**Fig 3:** Process carried out by robotic picking system in subsequent manner.

accuracy, velocity and resource effectiveness highlight its capacity to tackle significant obstacles in agriculture while preserving or enhancing the quality of harvested crops. The findings provide useful insights to the wider discussion on the implementation of AI in sustainable and efficient agriculture operations.

**Harvesting precision and adaptability**

The AI-powered robotic system's exceptional harvesting precision represents a significant advancement in the automation of bean crop harvesting. The machine learning algorithms' capacity to adapt to many bean types and growth stages is a remarkable accomplishment. The system's capacity to distinguish nuanced variations in crop attributes, such as hue and dimensions, demonstrates the strength of the underlying artificial intelligence models (Beloev *et al*., 2021). This level of precision has great potential in minimizing harvest loss and maximizing production, hence enhancing the overall efficiency of agricultural activities.

**Efficiency gains and throughput**

The significant decrease in the time required for harvesting, as accomplished by the robotic system in comparison to traditional manual methods, highlights the potential for enhancing efficiency in the production of legume crops on a wide scale. The combination of quickly and precisely identifying mature legumes, along with the agility of the robotic arm, leads to a significant boost in harvesting efficiency (Liakos *et al*., 2018). Efficiency plays a vital role in dealing with manpower shortages, enhancing the potential to expand legume cultivation and guaranteeing timely harvesting for optimal crop yields.

**Resource utilization and sustainability**

The analysis of resource usage emphasizes the environmentally aware design of the AI-driven robotic harvesting system. Adopting adaptive algorithms enhances energy efficiency, hence promoting sustainable agriculture methods. The system's little environmental impact, demonstrated by decreased soil compaction and minimal disruption to adjacent flora, is in line with the goal of promoting sustainable farming (Balaska *et al*., 2023). These findings indicated that incorporating AI into agricultural machinery can result in farming techniques that are more efficient in their use of resources and more environmentally sustainable.

**Comparative economic analyses**

The comparative economic assessments demonstrate the possibility for cost-effectiveness in the long run by implementing the AI-powered robotic system for harvesting legume crops. Although the initial setup costs are substantial, the efficiency improvements and decreased reliance on manual labor can lead to substantial long-term reductions in operational expenditures (Tian *et al*., 2020). The robotic system's economic feasibility, along with its increased crop output and reduced waste, makes it a key investment for farmers and agricultural enterprises aiming to improve productivity and financial gains (Javaid *et al*., 2023).

**Human-labor synergy**

A crucial element of the topic centres on the harmonious interaction between AI-driven robotic systems and human work. Although the robotic system exhibited autonomy in crop identification and harvesting, human supervision is crucial for system monitoring, maintenance and addressing unexpected obstacles (Othman and Yang, 2023). This partnership between humans and robots signifies a fundamental change in the way agricultural labor operates, highlighting the importance of enhancing the skills of the workforce to effectively handle and cooperate with modern AI technologies.

While recognizing the achievements, it is essential to confront the difficulties encountered during the experimentation. The ability of the robotic system to adjust to different environmental circumstances and crop structures is an aspect that still needs improvement. Continued research and development should prioritize improving the system's flexibility and resolving possible constraints, such as adverse weather conditions or irregular crop arrangements (Bhagat *et al*., 2022).

Based on the results of the study, potential future research avenues could involve investigating the incorporation of real-time decision-making abilities and advanced sensor technologies to further improve the autonomy and flexibility of the AI-driven robotic system. Furthermore, it is important to conduct inquiries into the social and economic consequences of widespread implementation, such as the possibility of job displacement and the dynamics of rural communities. This is necessary to achieve a comprehensive understanding of the technology's effects. In conclusion, the results of this study emphasize the significant capacity of AI-driven robotic systems in the harvesting of legume crops. The exhibited accuracy, productivity improvements and environmental friendliness are in line with the overarching objectives of contemporary agriculture. Although there are still difficulties, the progress outlined in this paper provides essential knowledge for the current discussion on incorporating AI in agriculture. This will lead to a more efficient, sustainable and technologically advanced future in growing and harvesting legume crops.

## MATERIALS AND METHODS

**Dataset**

The data is sourced from Github link [weedsData, Database for weed classification, Structures-Computer Interaction Laboratory, University of California, Los Angeles. https://github.com/StructuresComp/Multi-class-Weed-Classification/]. In this work, a part of data is used to detect dandelion weed and soybean using robot (Fig 4). The dataset is named AIWeeds which is collected from fields of North Dakota, California and Central China. The image resolution is 1920×1080 or 1280×720 pixels.

**Preprocessing of image dataset**

Image augmentation, scaling and dipping are all part of the preprocessing steps involved in learning. To avoid significant distortion, all images used for training, validation and testing were first rotated and shrunk to 224×224. The next step in the process was image augmentation, which included randomly rotating and scaling it both horizontally and vertically. Next, we divided the labeled images into sets for testing, training and validation. Each of these sets included an 80:20 ratio of the images for CNN modeling. To ensure that the weed class was distributed equally across each subgroup, stratified random partitioning was used. To monitor the training process and reduce over-tightening, a 10% validation dataset was created from a random split of 80% of the training dataset. The remaining 20% could never participate in any training process and were kept for testing. Generally, even after a lengthy training period on a computationally strong platform, training the models from scratch using a dataset cannot ensure satisfactory performance. As a consequence, before training using Keras, each model was loaded with the relevant pre-trained weights on ImageNet. The uniform distribution was used to initialize the weights of the fully-connected layer.

**4-Layer convolutional neural network (CNN) architecture**

This study uses a 4-layered convolutional neural network (CNN) to classify and identify weeds that damage soybean crops (Fig 5). As the name suggests, neural network approaches instruct the computer to process information in a way that reflects the organization of the human brain, which consists of many layers and linked neurons, or nodes. The way that information moves from the input layer to the output layer may be used to classify different neural network algorithms. Artificial Neural Networks (ANN), Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN) are a few neural network approaches. The CNN method, which consists of one output layer, many hidden layers and one input layer, is used to train the model. Convolutional layers, pooling layers and non-linear activation levels make up the hidden layers. To identify certain characteristics in the image, the convolutional layers apply a series of filters to the input data. Next, the data's dimensionality is decreased by the pooling layers and the model's ability to learn more intricate representations of the data is enhanced by the non-linear activation layers, which add non-linearity to the model. A fully connected layer called the CNN's output layer classifies an image according to its classifications. The model is a CNN model with four layers that are stacked on top of each other.

- Four Conv2D layers, with 4 activation functions ('relu') and 64, 64, 128 and 128 filters with a 3×3 size and a convolution operation applied to the input.
- Four MaxPooling2D layers, where each one performs a max pooling operation with a pool size of two by two to the output of the matching convolution layer.

**Fig 4:** Images of soybean (left) and Dandelion (right).

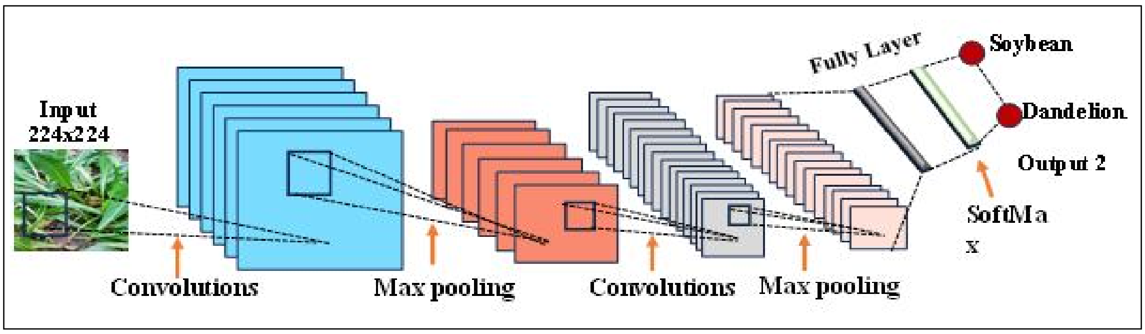


**Fig 5:** Architecture 4-layer CNN model.

- The output of the last pooling layer is transformed into a one-dimensional array by the first flatten layer. Which allows it to be fed into the dense layers.
- One dropout layer helps avoid overfitting by randomly setting a portion of input units to 0 at each training update.
- 1 Dense layer with 512 neurons that uses ReLU activation function to apply a fully connected operation on the dropout layer's output.
- One dense layer with four neurons that uses softmax activation function to apply a fully connected operation to the output of the preceding dense layer.

## RESULTS AND DISCUSSION

In this paper, a 4 layer- CNN model is architected for classification of dandelion and soybean images. The images are acquired using robot. After 25 training epochs, the neural network model exhibits impressive performance metrics (Fig 6). The training accuracy is 97.80%, signifying accurate classification of over 98% of the training data. While the training loss, a measure of the difference between predicted and actual values, is low at 0.1030. The model shows a little higher validation accuracy of 90.16% and a loss of 0.4758 on the validation front, indicating that it correctly classifies around 90% of unseen data objects.

A useful technique for evaluating a classification model's performance is a confusion matrix (Fig 7). The dandelion and soybean classes are the two classes on which the matrix specifically focuses. The values in the matrix are classified into four groups: false positives (FP), true negatives (TN), true positives (TP) and false negatives (FN). Here, the algorithm detects 1476 instances of soybean (TN) and correctly recognises 239 cases of dandelion (TP). On the other hand, it misclassifies two cases as soybean when they are really dandelion (FN) and mistakenly identifies one instance as dandelion when it is truly soybean (FP). Although the model performs well overall, with a high percentage of true positives and true negatives, these misclassifications point to possible areas for improvement, especially in differentiating between occurrences of dandelions and soybeans. The model might improve its accuracy and reduce classification mistakes with more refining and training rounds.

The report that is presented in Table 1 provides a thorough examination of the performance of a classification model. It measures accuracy, precision, recall and F1-score for two different classes: soybean and dandelion. With accuracy ratings of 0.9971 for both classes, the model performs well, successfully classifying about 99.71% of cases for each category.

The Dandelion and soybean precision ratings of 0.9917 and 0.9986, respectively, demonstrate the model's accuracy in identifying positive examples within each class. Furthermore, strong recall scores of 0.9917 and 0.9986 highlight the model's capacity to accurately represent the majority of real positive cases. The strong performance of the model is further validated by the F1-scores, which produce values of 0.9917 for broadleaf and 0.9986 for soybean. The F1-scores show a harmonised balance between accuracy and recall. The number of instances for each class is shown in the support column; broadleaf has 241 instances, whereas soybean has 1478 instances. Furthermore, the model consistently performs

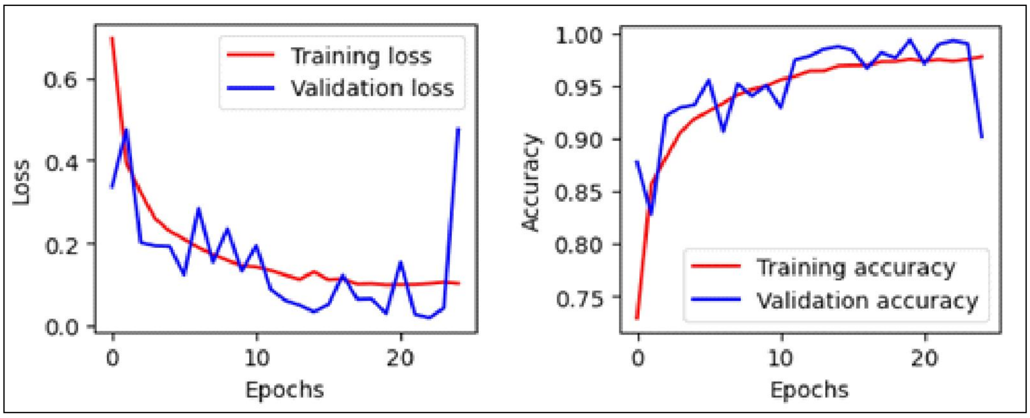


**Fig 6:** Loss and accuracy measurements.

**Table 1:** Classification report.

| Class | Accuracy | Precision | Recall | F1-score | Support |
|---|---|---|---|---|---|
| Dandelion | 0.9971 | 0.9917 | 0.9917 | 0.991 | 7241 |
| soybean | 0.9971 | 0.9986 | 0.9986 | 0.9986 | 1478 |
| Overall accuracy | 0.9971 | | | | |
| Micro avg | 0.9971 | 0.9971 | 0.9971 | 0.9971 | 1719 |
| Weighted avg | 0.9971 | 0.9970 | 0.9971 | 0.9970 | 1719 |

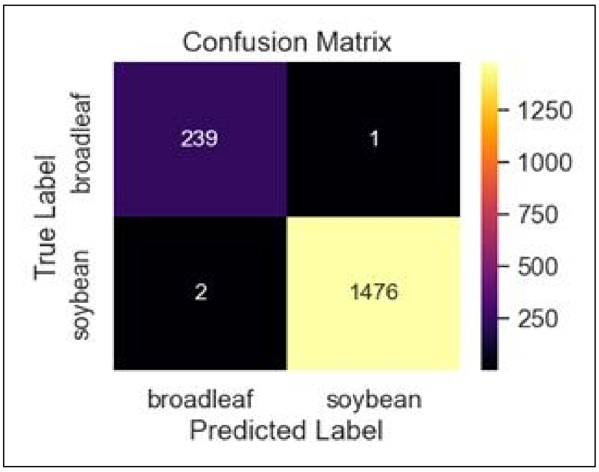


**Fig 7:** Confusion matrix for dandelion and soybean classes.

at a high level in all classes, as seen by its overall accuracy of 0.9971. This is supported by the weighted average and micro values as well, which are consistent with the overall accuracy and highlight the model's consistent performance in classification tasks. Overall, the report indicates how well the model differentiates between cases of dandelion and soybeans, providing important information on the model's generalisation and dependability.

## CONCLUSION

In conclusion, this study uses a 4-layer CNN architecture and obtains an overall accuracy of 99.71%. Robotic equipment was used to gather the soybeans and dandelions that make up the dataset. Stratified partitioning and image scaling are instances of this preprocessing. A confusion matrix and comprehensive performance report are used to assess the model's performance, which shows strong metrics for accuracy, precision, recall and F1-score. Overall, the research provides useful implications for agricultural management by demonstrating the CNN model's efficacy in classifying weeds. In the future, a diverse dataset will be used to enhance the ability of the prediction model.

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**Author contributions**

The authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

**Data availability statement**

Not applicable.

**Declarations**

Authors declare that all works are original and this manuscript has not been published in any other journal.

**Conflict of interest**

The authors declare that they have no conflict of interest.

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